DOCTORAL THESIS

Operational Energy Performance Assessment Methods for Credible Energy Certificates Based on Metered Energy in Non-Residential Buildings

Helena Kuivjõgi

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Declaration:
Hereby I declare that this doctoral thesis, my original investigation and achievement, submitted for the doctoral degree at Tallinn University of Technology has not been submitted for doctoral or equivalent academic degree.

Helena Kuivjõgi

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signature

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Mitteeluhoonete mõõdetud energiakasutusel põhineva energiamärgise hindamise meetodid

HELENA KUIVJÕGI

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The list of the author's publications on which this thesis is based:

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II H. Kuivjõgi, J. Kurnitski, A. Uutar, and M. Thalfeldt. NZEB and market-based renovation case study of an existing office building. *E3S Web Conf.*, 246:05002, 2021.

III H. Kuivjõgi, J. Laaneste, M. Thalfeldt, and J. Kurnitski. Heat recovery ventilation system heating energy weather normalization – calculation method and case study. *E3S Web Conf.*, 362:09003, 2022.

IV H. Kuivjõgi, S. Vasman, E. Petlenkov, M. Thalfeldt, and J. Kurnitski. Data-driven baseline generation for post-retrofit energy saving assessment, a comparison of statistical and machine learning methods. *Journal of Building Engineering*, 98:111016, 2024.

V H. Kuivjõgi, M. Thalfeldt, and J. Kurnitski. Metered Energy Normalization in Non-residential Buildings for Compliance Assessment with EPBD Minimum Energy Performance Standards. In Claudio Zilio, Filippo Busato, Livio Mazzarella, and Marco Noro (eds.), *Proceedings of the 15th REHVA HVAC World Congress – CLIMA 2025*, pp. 880–889. Springer Nature Switzerland, Cham, Switzerland, 2026.

VI H. Kuivjõgi, K. Ahmed, M. Thalfeldt, and J. Kurnitski. Metered energy ratings normalisation methods for operational hours and EPB energy in non-residential buildings. Under review at *Energy Reports*, 2026.

Author's Contributions to the Publications

I In Publication I, the author of the thesis was the main author; she collected the data, carried out the analysis, prepared the figures, and wrote the manuscript.

II In Publication II, the author of the thesis was the main author; she collected and pre-processed the raw data, developed and calibrated the simulation model, carried out the calculations and analysis, prepared the figures, and wrote the manuscript.

III In Publication III, the author of the thesis was the main author; she collected and pre-processed the raw data, implemented the calculation model in R, carried out the analysis, prepared the figures, and wrote the manuscript.

IV In Publication IV, the author of the thesis was the main author; she collected the raw data, developed and calibrated the simulation models, implemented the monthly-based statistical degree-day method, carried out the analysis, prepared the figures, and wrote the manuscript.

V In Publication V, the author of the thesis was the main author; she collected and pre-processed the raw data, developed the simulation model, developed the operational-hours adjustment method, carried out the analysis, prepared the figures, and wrote the manuscript.

VI In Publication VI, the author of the thesis was the main author; she collected and pre-processed the raw data, developed and calibrated the University Facility simulation model, implemented the normalisation methods, carried out the analysis of the results, prepared the figures, and wrote the manuscript.

Introduction

Greater energy efficiency and the use of renewable energy sources are essential for reducing greenhouse gas emissions caused by human activity. [1, 2] As buildings account for 36 % of greenhouse gas emissions in the European Union (EU), the EU has introduced the Energy Performance of Buildings Directive (EPBD), which now aims for a fully decarbonised building stock by 2050. The 2024 recast of the EPBD introduces new requirements for existing buildings, including Minimum Energy Performance Standards (MEPS) for the worst-performing non-residential buildings, with the objective of renovating at least 16 % of the worst-performing stock by 2030 and 26 % by 2033. [3]

The energy renovation need in the Estonian commercial building market is approximately 17 million m^2 of floor area in order to achieve the climate neutrality targets by 2050. However, in 2020 the major renovation rate was approximately four times lower than required to meet these objectives. [4] Therefore, an overview of current renovation practices in Estonian commercial buildings and a better understanding of how to achieve the renovation targets defined by MEPS are needed.

To move towards climate neutrality, it is first necessary to know how energy-efficient buildings are today. It is also necessary to overcome the barriers preventing commercial buildings from being renovated to the nearly zero energy building (NZEB) level required by the EPBD. In practice, a performance gap may occur when the measured energy performance of a building differs from the expected or calculated performance. In non-residential buildings, this gap is common, but its causes vary between buildings and may be related to technical system operation, occupant behaviour, non-regulated energy uses, operational hours, weather conditions, or other operational factors.

Progress in energy efficiency must therefore be measured both at the building level, using baseline values or thresholds, and on national and international scales, using consistent energy performance of buildings (EPB) assessment methods. In the EU, the thresholds for the worst-performing buildings are based on energy performance certificates (EPCs), which are benchmarking and rating instruments relying on total primary energy use in kWh/m^2a as the standard indicator of building performance. The EPBD also requires Member States to develop methods that consider the influence of occupant behaviour and local climate when metered energy use forms the basis for calculating the EPB.

Weather normalisation of metered energy use is important for energy labelling and comparison, as well as to improve the energy performance of existing and future buildings. To adequately assess changes in energy use due to building renovation, an energy use baseline must be established, which can be done by calculating weather-normalised energy use or by developing a model for pre-retrofit energy use. As buildings become more advanced and incorporate smart energy meters, obtaining the necessary data becomes easier, making the application of data-driven methods more feasible and attractive. However, older buildings often have limited data availability and lack sub-metering, which highlights the need for robust methods that can also use monthly energy bills or main-meter data.

When EPCs are based on metered energy use, the measured data may include energy uses that are outside the EPB scope and may also reflect deviations from typical building use. This is particularly important in non-residential buildings, where tenant activities, extended operational hours and non-regulated electricity use can strongly influence measured energy performance. As approximately ten Member States in the EU, including Estonia, calculate operational EPCs using metered data, robust normalisation methods are needed to improve the comparability and credibility of metered-energy-based assessment.

The objective of this thesis is to improve the accuracy of energy performance assessment for non-residential buildings by developing methods for normalising metered

energy use using both simulation-based methodology and measured data. The main outcome of this thesis is an operational energy performance assessment methodology for non-residential buildings, together with a better understanding of how simulation-based methodology can support credible EPB assessment.

The main objectives of the thesis are:

1. To analyse the current energy use and renovation practices of commercial buildings in Estonia and identify the barriers limiting renovation to the nearly zero energy building (NZEB) level. (Publication I)
2. To quantify the gap between market-based renovation outcomes and NZEB renovation targets in non-residential buildings. (Publications: I, II)
3. To analyse cost-optimal solutions to improve the energy performance of major NZEB-level renovation in office buildings. (Publication II)
4. To develop and evaluate methods for normalising metered energy use to typical weather and use conditions for operational energy performance assessment in non-residential buildings. (Publications: III, IV, V, VI)

Research questions

1. What are the main barriers preventing commercial buildings from being renovated to the NZEB-level required by the EPBD?
2. What are the cost-optimal renovation measures for achieving major NZEB-level renovation in office buildings?
3. How accurate and applicable are simple degree-day methods for weather normalisation of heating energy use compared with more advanced data-driven methods?
4. How can metered energy use be transformed to correspond to the EPB assessment boundary and typical building use?
    (a) How can energy used to condition the indoor environment be separated from total metered energy data?
    (b) How can tenant electricity meter data be utilised to complement main-meter data for considering the influence of occupant behaviour in issuing an EPC?
    (c) If operational hours differ from typical use, how can energy use be adjusted to correspond to typical conditions?

The thesis is based on three peer-reviewed journal articles and three conference papers.

In Publication I, we analysed the market-based renovation in reference office buildings, grocery stores and hardware stores. The goal was to provide input for the development of NZEB renovation incentives of commercial buildings. We quantified the energy performance before and after common market-based renovations to indicate the gap between market-based renovation and major NZEB-level renovation, as required in the EPBD. We interviewed the stakeholders to acquire an understanding of why they are overlooking renovation to NZEB. Furthermore, we identified the scope and cost of deeper renovation measures to achieve major NZEB-level renovation.

In Publication II, we analysed measured energy use and used a calibrated simulation model to identify energy renovation measures and savings to improve the energy performance to the NZEB level in a large office building. We considered different energy improvements and their costs to increase the energy efficiency and achieve the C-level (threshold is 160 kWh/m^2) of the reference building. Several measures were selected by the suggestion of energy audits, the knowledge of the authors, and measures earlier studied in Publication I were improved.

In Publication III, we developed a new analytical model for weather normalisation of heating consumption for an air handling unit with regenerative rotor heat exchanger. The new method was compared with the traditional heating degree-day (HDD) method and normalisation aspects were analysed. The real capacity calculation that was calibrated with hourly measured ventilation heating and electricity energy data was used to imitate real air handling unit (AHU) heater energy need.

In Publication IV, we compared degree-day and machine learning methods for predicting the baseline of building energy use, which serves as the reference energy use for post-retrofit savings assessment. We benchmarked the newer machine learning approach, including clustering and regression modelling using hourly-basis heating and electricity data, against the monthly-based statistical degree-day method, a robust and well-established benchmark in the industry.

In Publication V, we developed the methodology for normalising metered heating and electricity energy use to make it comparable to standard energy use, considering the difference between occupied and operational hours. We used a calibrated simulation model with different user and electricity profiles to validate the methodology.

In Publication VI, we developed two previously unformalised normalisation procedures for assessing building energy performance using metered data: adjustments for non-EPB energy and typical operational hours. The methods were applied to metered energy use from trade and office/educational buildings and validated with simulation models of reference buildings.

Practical outcome and novelty of the thesis:

- **Contribution to knowledge:** A systematic assessment of the gap between market-based renovation and major NZEB-level renovation in Estonia, as required by the EPBD. The analysis identifies key barriers to deep renovation, including the structure of rental and energy costs, the high investment cost of NZEB renovation, and uncertainties associated with EPC assessment methods. Furthermore, the thesis contributes to bridging the gap between design-based and operational energy performance assessment by combining simulation-based methods with normalisation of metered energy use, thereby enabling more accurate and policy-relevant evaluation of commercial building energy performance.

- **Methodological novelty:** Contribution to the assessment of renovation impact and operational energy savings by providing additional insights into the selection of energy-use modelling methods for weather normalisation. Development and validation of an analytical method for weather normalisation of AHU heating energy and formalised procedures for separating non-EPB energy use using tenant-level metering and adjusting metered energy use to standard operational hours.

- **Contribution to practice:** A detailed case study on the cost-optimal renovation pathway to NZEB in an office building is presented, demonstrating the combination of measures required to achieve target performance and highlighting the economic limitations of deep renovation under current market conditions. A methodological

workflow for simulation-based EPB assessment was also developed, using measured energy data to calibrate the simulation model.

- **Contribution to policy and impact:** Formalised normalisation procedures for metered energy use were developed as an additional application to the existing national energy performance assessment methodology. These procedures improve the accuracy and comparability of EPCs by accounting for non-EPB energy use and deviations from standard operational conditions, thereby enabling more reliable use of measured energy data in regulatory assessment.

Limitations and future work

This thesis has several limitations that should be considered when interpreting the results. The market-based renovation analysis was based on a sample of Estonian educational, office, grocery and hardware store buildings and reflects the regulatory framework, climate conditions and commercial real-estate market characteristics prevailing in Estonia; therefore, the findings may not be directly transferable to other countries. The renovation and cost-optimality analyses relied on reference buildings, calibrated simulation models, energy audits and stakeholder interviews, which inevitably include uncertainties related to future energy prices, investment costs, occupant behaviour, weather conditions, equipment performance and financial assumptions. The normalisation methods were developed and validated using a limited number of reference buildings and assumed the availability of sufficiently detailed metering, operational schedules and building information. In practice, such data may not always be available, which can limit the applicability and accuracy of the methods. The non-EPB energy separation procedure depends on the representativeness of tenant-meter data and assumptions regarding end-use allocation, while the operational-hours adjustment assumes that occupancy schedules and power loads adequately represent actual building operation. The weather-normalisation and baseline-generation studies were validated primarily with measured and simulated data from a small number of non-residential buildings, and therefore additional validation across a wider range of building types, climates and operational conditions is required. Finally, although the proposed methods improve the comparability of metered-energy-based EPC assessment, they do not eliminate all uncertainty associated with occupant behaviour, tenant activities, future changes in building use, or the inherent limitations of simulation-based performance assessment.

Abbreviations and terms

AHU air handling unit

ASHRAE American Society of Heating, Refrigerating and Air-Conditioning Engineers

BMS building management system

CHP Combined Heat and Power

CV(RMSE) Coefficient of Variation of the Root-Mean-Square Error

DCV demand-controlled ventilation

DHW domestic hot water

EPB energy performance of buildings

EPBD Energy Performance of Buildings Directive

EPC energy performance certificate

EU European Union

HDD heating degree-day

HVAC heating, ventilation and air conditioning

IEQ indoor environmental quality

IRR internal rate of return

MEPS Minimum Energy Performance Standards

NMBE normalised mean bias error

NPV net present value

NZEB nearly zero energy building

PE primary energy

PV photovoltaic

REHVA The Federation of European Heating, Ventilation and Air Conditioning Associations

SEER Seasonal Energy Efficiency Ratio

SFP specific fan power

TRY Test Reference Year

VAV variable air volume

Symbols

Symbol	Meaning
c	Specific heat capacity of air, kJ/(kg·K)
C_t	Annual energy cost in year t, €
C_0	Initial investment cost, €
CV(RMSE)	coefficient of variation of the root mean square error, %
c_DD	normalisation coefficient of degree days, -
E_{adj}	Energy use adjusted to standard operational hours, kWh/a or kWh/m^{2}a
$E_{\text{adj,el}}$	Electricity energy use with non-EPB energy excluded, kWh/a or kWh/m^{2}a
E_{base}	Building base energy use, kWh/month or kWh/m^{2}month
$E_{\text{baseline.month}}$	Weather-normalised energy use baseline monthly value, kWh/month or kWh/m^{2}month
E_{daily}	Daily total energy use from main meters, kWh/day or kWh/m^{2}day
$E_{\text{daily,base}}$	Lowest daily energy use from main meters, kWh/day or kWh/m^{2}day
E_{main}	Total energy use from the main meter, kWh/a or kWh/m^{2}a
E_{month}	Monthly total energy use from main meters, kWh/month or kWh/m^{2}month
$E_{\text{non-EPB},i}$	Energy use of non-EPB service i, kWh/a or kWh/m^{2}a
$E_{\text{norm.month}}$	Weather-normalised monthly total energy use, kWh/month or kWh/m^{2}month
$E_{\text{norm.weatherdependent}}$	Weather-normalised monthly weather dependent energy use, kWh/month or kWh/m^{2}month
$E_{\text{SpecificY.month}}$	Weather-normalised energy use baseline monthly value projected to a specific year, kWh/month or kWh/m^{2}month
$E_{\text{tenant},j}$	Tenant electricity use measured by tenant meter j, kWh/a or kWh/m^{2}a
$E_{\text{tenant,STD},j}$	Standard tenant appliances and lighting electricity use for tenant j, kWh/a or kWh/m^{2}a
$E_{\text{weatherdependent}}$	Monthly weather dependent energy use, kWh/month or kWh/m^{2}month
E_{we}	Weighted energy performance indicator (EPC), kWh/(m^{2}a)
$E_{\text{we,adj,wnorm,H,cr},j}$	Adjusted and weather-normalised heating energy use for carrier j, kWh/(m^{2}a)
$E_{\text{we,adj,el},j}$	Adjusted electricity energy use, kWh/(m^{2}a)
$E_{\text{we,DHW,cr},j}$	Domestic hot water energy use for carrier j, kWh/(m^{2}a)
f	Inflation rate, %
HDD_{Real}	Heating degree days of the real year, °C·d
HDD_{TRY}	Heating degree days of the test reference year, °C·d
IRR	Internal rate of return, %
IRR_R	Real internal rate of return, %
NMBE	Normalised mean bias error, %
NPV	Net present value, €
$P_{\text{non.op},i}$	Average non-operational load in month i, W
$P_{\text{op},i}$	Average operational load in month i, W
PE_{cr}	Primary energy factor of heating energy carrier cr, -

Symbol	Meaning
$\mathrm{PE}_{\mathrm{el}}$	Primary energy factor of electricity, -
Q_v	AHU heating energy use, kWh
$Q_{v,\mathrm{HDD,corrected}}$	HDD-normalised AHU heating energy use, kWh
q_v	Ventilation air flow rate, m^3/s
RMSE	Root mean square error
t_i	Total number of hours in month i, h
T_{exhaust}	Exhaust air temperature, °C
$T_{\mathrm{exhaust,lim}}$	Minimum exhaust air temperature limit, °C
T_{extract}	Extract air temperature, °C
$T_{\mathrm{out,real}}$	Outdoor dry-bulb temperature of the real year, °C
$T_{\mathrm{out,TRY}}$	Outdoor dry-bulb temperature of the test reference year, °C
T_{supply}	Supply air temperature, °C
T	Analysis period (for NPV calculation), years
τ_d	Standard operational hours per day, h/day
τ_i	AHU operation rate, -
τ_w	Standard operational days per week, d/week
$\Delta\Phi_{\mathrm{TRY,Real}}$	Difference in ventilation air heat capacity between TRY and real climate, kW
η_{hx}	AHU heat recovery efficiency, -
$\Phi_{h,\mathrm{corrected}}$	Weather-corrected ventilation air heat capacity, kW
$\Phi_{h,\mathrm{real}}$	AHU heating power calculated from metered data, kW
$\Phi_{h,\mathrm{Real}}$	Calculated ventilation air heat capacity in the real climate, kW
$\Phi_{h,\mathrm{TRY}}$	Calculated ventilation air heat capacity in the test reference year climate, kW
ρ	Density of air, kg/m^3

1 Background

1.1 Energy use and decarbonisation of non-residential buildings

Energy efficiency has been a central issue since the 1970s energy crisis, which showed that energy should not be treated as an unlimited resource. Since then, international and national policies have increasingly focused on reducing energy use, improving efficiency, and lowering greenhouse gas emissions. [1, 5, 6, 7]

A significant milestone was the Paris Agreement, adopted by 195 Parties at the United Nations Climate Change Conference in 2015. [8] The Agreement established the objective of holding the increase in global average temperature to well below 2°C above pre-industrial levels and pursuing efforts to limit warming to 1.5°C. [9] Building on this framework, the International Energy Agency (IEA) published the report *Net Zero by 2050: A Roadmap for the Global Energy Sector* in 2021, outlining milestones for achieving net-zero CO_2 emissions. The report emphasised the key role of governments in promoting energy efficiency and highlighted building energy performance certificates, green lease agreements, green bond financing and pay-as-you-save models as important instruments supporting the transition. [10]

The building sector is responsible for approximately 36% of CO_2 emissions in the EU. Non-residential buildings account for approximately 25% of the total building floor area in Europe. Wholesale and retail buildings represent the largest category (28%), followed by office buildings (23%) and educational buildings (17%). However, the specific energy use of non-residential buildings is at least 40% higher than that of residential buildings. This is mainly due to higher internal loads, more energy-intensive technical systems, and, in many building types, substantial non-EPB energy uses that are uncommon in residential buildings. Furthermore, during the last two decades, electricity consumption in the sector has increased significantly (74%) due to the growth of information technology equipment, data centres and air-conditioning systems. [11, 12] The distribution of energy end-uses differs considerably between non-residential building types and is strongly influenced by occupants' activities and process-related electricity use. Furthermore, Stensson [13] found that energy use in shopping malls is dominated by tenant-related electricity consumption, mainly lighting, and cooling-related energy use resulting from heat gains generated by lighting, appliances and occupants. In grocery stores, refrigeration has a major impact on electricity consumption and typically accounts for 50-60% of total electricity use. [14, 15]

Deep renovation is needed to reduce the final energy use of buildings and to contribute to greenhouse gas emission reduction targets. In residential buildings, renovation practice has commonly focused on improving the thermal performance of the building envelope through additional insulation and window replacement, together with the renovation of heating, ventilation and air conditioning (HVAC) systems where applicable. These measures are also relevant for non-residential buildings. However, commercial buildings differ from residential buildings because their energy use and renovation decisions are strongly influenced by internal layout, tenant activities, comfort requirements, lighting, HVAC design and ventilation systems. Consequently, market-based renovation in commercial buildings has mainly focused on measures with relatively short payback times, such as lighting replacement, building automation, demand-controlled ventilation, HVAC control improvements and selected technical-system upgrades. These characteristics explain the need to investigate renovation measures specifically in non-residential buildings and to assess how current market-based renovation practice contributes to energy performance improvement. [16, 17, 18]

1.2 Evolution of building energy performance regulation

Before the Paris Agreement, building energy efficiency in Europe was primarily regulated through national building codes and standards, which defined minimum requirements for building envelopes and technical systems. Energy performance assessment methods and asset ratings existed in several countries, but their implementation and scope varied.

A major milestone was the Council Directive 93/76/EEC (SAVE programme), adopted in 1993 to limit carbon dioxide emissions through improved energy efficiency. [19] This was followed by the EPBD in 2002, which introduced the requirement to calculate an EPC when constructing, selling or renting a building. The EPC became the main regulatory instrument for assessing and communicating building energy performance across the EU. Subsequent revisions strengthened energy performance requirements and introduced the concept of NZEB, which became the target level for new buildings and a reference level for major renovations. Major renovation means the renovation of a building where: (i) the total cost of the renovation relating to the building envelope or the technical building systems is higher than 25% of the value of the building, excluding the value of the land upon which the building is situated; or (ii) more than 25% of the surface of the building envelope undergoes renovation. [20]

In 2007, the European Commission adopted an Action Plan targeting a 20% reduction in energy consumption by 2020. [21] These objectives have since been progressively strengthened, with the 2024 revision of the EPBD aiming for a fully decarbonised building stock by 2050. [22] Under the revised directive, Member States must adopt national energy performance assessment methodologies, introduce MEPS for non-residential buildings, and renovate at least 16% of the worst-performing building stock by 2030 and 26% by 2033 (Figure 1). [23] As MEPS are implemented through EPC-based thresholds, the reliability and comparability of EPC assessment methods become increasingly important for policy implementation and renovation decision-making.

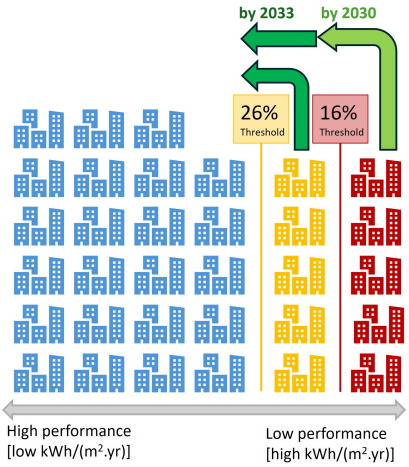


Figure 1: Non-residential building renovation plan - 16 % of worst-performing buildings renovated by 2030 and 26% by 2033 (adapted from [24])

Similar long-term decarbonisation strategies have also been adopted in other regions. In the United States, states and local governments have established greenhouse gas reduction targets extending to 2050. [25] In Australia, the Energy Efficiency Council published the Australian Energy Efficiency Policy Handbook in 2016, outlining actions required to achieve long-term productivity and energy efficiency goals. [26]

1.3 Energy performance assessment methods

The EPC relies on total primary energy use expressed in kWh/m^2a as the standard indicator of building performance. According to Annex I of the EPBD, the calculation methodology may be based on calculated or metered energy use and shall reflect typical energy use for heating, cooling, ventilation, domestic hot water (DHW), lighting and other technical systems related to indoor environmental quality (IEQ). In other words, the assessment includes services related to the EPB while excluding non-EPB services, such as office equipment, catering and computer rooms. [3, 23, 27]

ISO 52000-1 [28] specifies different types of assessment per application. Generally, there are two types of EPB assessment: (i) calculated, based on calculated energy use, or (ii) measured (operational), based on measured energy use. A calculated EPC is based on calculated energy performance using standardised boundary conditions, occupancy schedules and user profiles. Its purpose is to assess the energy efficiency of a building and its technical systems, independent of user and weather conditions. An operational EPC, in contrast, is based on measured energy use and therefore reflects the actual performance of the building in operation.

Approximately ten Member States in the EU currently calculate operational EPCs using metered energy data, whereas others rely primarily on calculated as-designed or as-built performance values. Metered data provide direct information on actual building energy use and offer a cost-effective basis for benchmarking, policy implementation and verification of renovation outcomes. However, the scope of the EPBD is limited to energy use associated with conditioning the indoor environment under typical weather and user behaviour conditions, whereas metered energy data often include energy uses outside this scope.

In Estonia, operational EPCs are calculated from metered energy use, excluding non-EPB energy use if separately measured. In practice, however, non-EPB energy use is rarely sub-metered. This is often because installing dedicated meters is not considered cost-effective. Before the methods developed in this thesis were incorporated into the regulations, heating energy use was normalised to a typical year using HDDs, but no other normalisation methods were specified. Benchmarks are fixed limits by building type and are intended to represent typical building performance. This approach may lead to discrepancies between measured and typical energy use, particularly in retail and office buildings with refrigeration systems, server rooms or extended operating hours. [29, 30, 31]

This creates a fundamental challenge for operational EPC methodologies. To ensure comparability between buildings and consistency with EPBD requirements, measured energy use must be normalised to account for weather variations, deviations in occupancy and operational schedules, and energy uses outside the EPB scope. Therefore, reliable normalisation procedures are required before metered energy data can be used for regulatory assessment and benchmarking purposes.

1.4 Occupancy, tenant electricity use and behavioural impact

Occupant behaviour has a particularly strong impact on the performance gap in commercial buildings. Occupants influence building energy use through their interaction with building systems, occupancy schedules and operational practices. As a result, actual energy use may differ substantially from the standardised assumptions used in energy performance assessment. [29, 32, 33, 34, 35]

Masoso et al. studied five African commercial buildings and found that 56% of electricity was consumed during non-working hours, with base loads ranging from 8-18 W/m^2, mainly

caused by equipment such as computers and air conditioners left switched on [36]. Similarly, Menezes et al. used Post-Occupancy Evaluation (POE) data to investigate the building energy performance gap in an office building. They found that actual occupancy periods were considerably longer than standard occupancy schedules used in energy calculations. A model based on design parameters and standard occupancy assumptions explained only one-third of the actual energy use, whereas a model incorporating measured occupancy and sub-metered energy data reduced the deviation to approximately 3%. These results demonstrate that occupancy and operational schedules have a major influence on building energy use and that POE data can improve the accuracy of energy performance assessment and simulation models [32].

Furthermore, in non-residential buildings, tenant-related electricity use may constitute a substantial share of total energy consumption. Office buildings often include server rooms, associated cooling, office equipment and extended plug loads which may account for approximately 40% of total energy use, while retail buildings may contain refrigeration systems (about 47% of total energy use) and tenant-specific lighting. [14, 37] These loads are typically outside the EPB scope but are often included in metered energy use recorded by main meters. Consequently, tenant electricity use can significantly influence measured energy performance and contribute to discrepancies between calculated and operational EPC values.

1.5 Performance gap in non-residential buildings

The performance gap has been recognised since the 1990s, when energy savings from household retrofits were often smaller than predicted [1], and a low-energy office building consumed energy more than twice the expected amount of energy [38]. In 2001, Bordass et al. studied 16 commercial buildings and found that actual energy use was generally higher than anticipated, indicating that energy was often poorly specified in design criteria [39]. Later reviews, such as Mahdavi et al., confirmed that the median performance gap was 14% ± 27% [29].

The performance gap arises from several factors: climate and environmental conditions, regulations and calculation methodologies, building design and construction (architecture, building physics, HVAC systems) [29, 40], and user-related behaviour. User-related aspects may include unnecessary non-EPB loads (e.g., computer rooms, catering, office equipment), which can add 25–80% to normal building services [39], as well as DHW use, internal gains, indoor temperature adjustments, and atypical operational hours [41].

Reducing the performance gap requires more accurate asset rating inputs [42], the integration of POE data [29, 35] and comprehensive guidelines to support energy assessors [43, 44]. While asset ratings are useful indicators during the design phase, they rely heavily on assumptions and standardised parameters, which limits their ability to reflect actual building performance.

1.6 Economic barriers and cost-optimality of major energy renovation

The energy renovation need in the Estonian commercial building market is approximately 17 million m^2 of floor area in order to achieve the climate neutrality targets by 2050. However, the major renovation rate in 2020 was approximately four times smaller than required to meet these objectives. [4] In Estonia, the cost-optimal NZEB target for major renovation, typically involving renovation of the building envelope and HVAC systems, is EPC class C. This is hereafter referred to as NZEB-level renovation.

Several studies have reported that many barriers exist in the commercial building

renovation market. For example, barriers frequently highlighted are: insufficient knowledge about actual building energy performance, an inefficient certification system, uncertainty regarding the return on investment and how organisations develop best practices of energy management [45, 46].

Hinnells et al. [12] show that the energy costs are usually less than 5% of the cost of operating a building. The Federation of European Heating, Ventilation and Air Conditioning Associations (REHVA) states in the Guidebook [47] that in a traditional building the rent could be 300 €/m^2 (without value-added tax (VAT)), including maintenance of 10 €/m^2, and energy for 20 €/m^2 annually. Therefore, energy costs represent only a small fraction (6%) of total occupancy costs, reducing the financial incentive for tenants to invest in energy-efficiency improvements.

Energy retrofit investments are associated with several sources of uncertainty, like unpredictable weather data, building envelope thermal properties, installation efficiency, energy use, occupant behaviour or financial and economic parameters (energy prices or discount/growth rates). Therefore, uncertainty can increase the cost of capital for energy efficiency investments and needs to be considered in financial analysis [48, 49].

Furthermore, Stensson found out that less than half of the energy audits for shopping malls included cost-optimal energy efficiency measures. This highlights the need for further research on cost-optimal renovation measures and the role of advanced metering, monitoring and control systems in improving building energy performance. [13]

Gohardani et al. [50] carried out ten interviews with different stakeholders in Denmark that confirm these barriers. In addition, it was found that the EPC of a building is not a motivator for energy renovations because it is primarily based on the calculated energy use, which might substantially deviate from measured energy use.

The barriers identified in the literature suggest that achieving NZEB renovation is not solely a technical challenge but also an economic and organisational one. Even when technically feasible solutions are available, investment decisions are strongly influenced by ownership structure, tenant–landlord relationships and uncertainty regarding future energy savings. Consequently, the energy performance achieved through market-based renovation may differ substantially from the performance level required to meet NZEB targets.

1.7 Normalisation of metered energy use for energy performance of buildings assessment

The use of metered energy data has increased in both renovation impact assessment and operational energy performance assessment. However, measured energy use reflects not only the physical characteristics of the building and its technical systems, but also external factors such as weather conditions, occupancy patterns and operational practices. Consequently, direct comparison of measured energy use between years or buildings may lead to misleading conclusions. Normalisation is therefore required to adjust measured energy use to common reference conditions and enable a fair comparison of building performance.

To assess renovation impact, an energy use baseline must be established. This can be achieved through weather normalisation or by developing predictive models for pre-retrofit energy use using methods such as linear regression, change-point linear models, degree-day methods or machine learning algorithms. The resulting baseline enables the assessment of energy savings and changes in energy use after renovation.

As buildings become more advanced and incorporate smart energy meters, obtaining the necessary data becomes easier, making the application of data-driven methods more

feasible and attractive. Current approaches utilise data with varying time resolutions, from monthly utility bills [51] to 15-minute measurements [52]. Nevertheless, the degree-day method remains widely used because of its simplicity and limited data requirements. More advanced approaches include linear and change-point regression models recommended by the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) [53], including those implemented in the ASHRAE Inverse Modeling Toolkit [54].

In Publication IV, the degree-day method was compared with a machine learning approach for establishing energy use baselines. The machine learning workflow consisted of data pre-processing, clustering and scenario-specific regression modelling. Input data included weather variables and hourly metered energy use. The pre-processing stage generated additional weather- and occupancy-related features to improve prediction accuracy. The resulting hourly predictions were aggregated to monthly values and compared with the monthly degree-day method. [55]

Non-residential buildings often operate beyond the schedules assumed in standards and energy performance calculations, which may significantly influence measured energy use and operational EPC values. While weather normalisation methods are widely established, considerably less attention has been given to the impact of operational hours on energy performance assessment. Existing benchmarking systems in Ireland and the United States utilise adjusted benchmarks for buildings with extended occupancy hours. [56, 57] Swedish regulations allow adjustments of heating and cooling energy for buildings with unusual internal loads. [58] However, there remains a lack of robust methods for adjusting metered energy use to typical operational conditions within the European EPC framework.

2 Methods

2.1 Overall research design

This thesis addresses the situation prevailing in the energy use and renovation of non-residential buildings and develops methods for assessing measured energy use in a way that is compatible with EPBD and Estonian EPC requirements. The work is divided into two main parts. The first part addresses why commercial buildings are not renovated to the NZEB level required for major renovation (later NZEB renovation level). Building samples and interviews were used to study how commercial property companies deal with the renovation need in their buildings in Estonia. In addition, one reference building was used to analyse cost-optimal renovation solutions for achieving the NZEB renovation level. The second part focuses on the methodological challenge of measured energy assessment: metered energy use may include energy uses that are not associated with conditioning the indoor environment, and actual operation may differ from typical use. Therefore, when EPCs are based on measured energy use, normalisation is required to separate energy use of the EPB scope from main meter data and to adjust the energy use for weather conditions and deviations from typical operation.

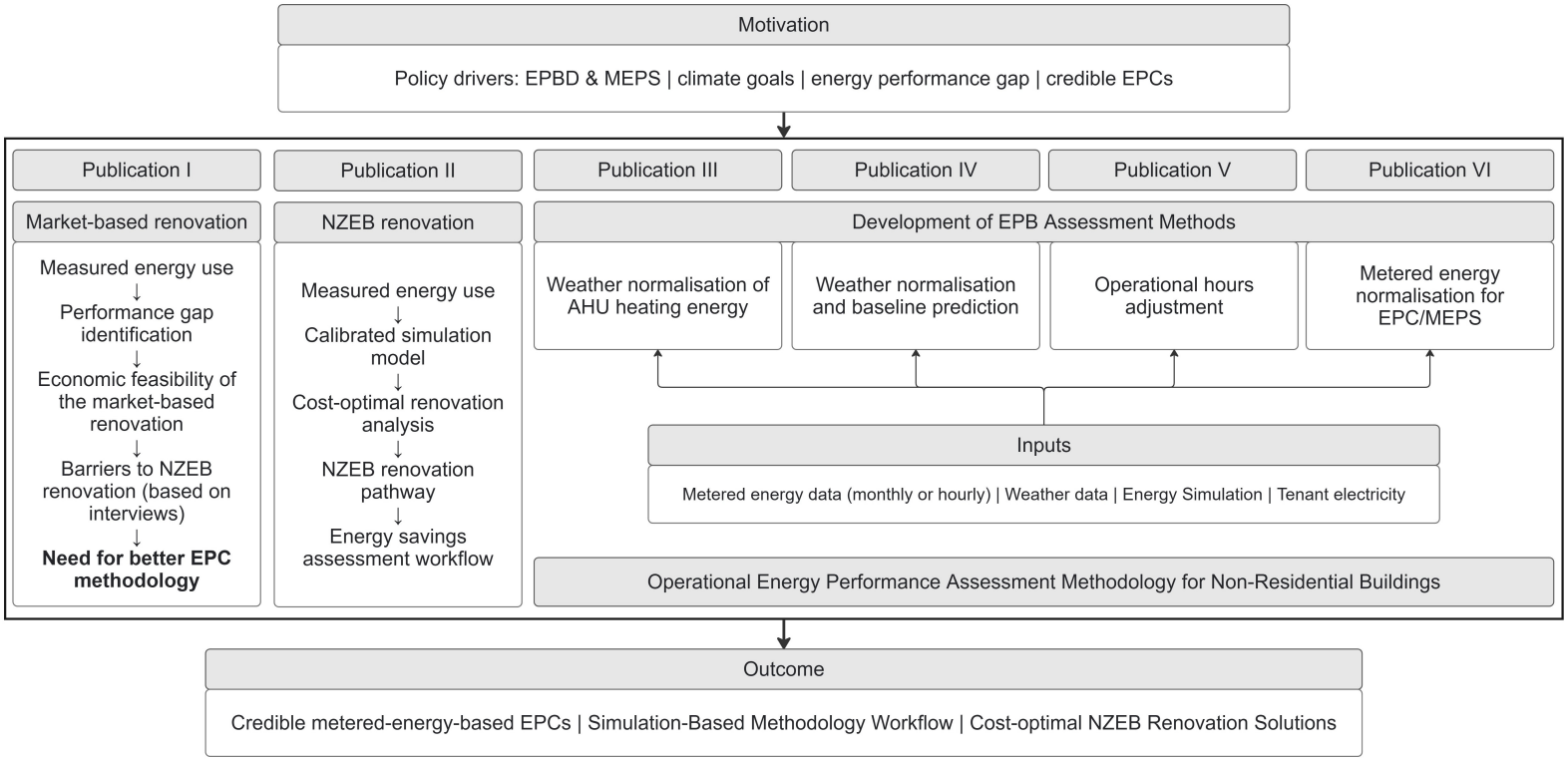
The overall workflow is shown in Figure 2 and it comprises five methodological components. First, measured delivered energy data were collected from reference buildings, primarily from energy invoices, main meters, sub-meters and building management systems, and were analysed accordingly. Second, the economic feasibility of the market-based renovation was assessed using indicators such as investment cost, energy cost and savings, payback time and internal rate of return (IRR). Third, where detailed investigation was needed, energy simulation models were developed and calibrated against the measured energy use using actual or typical weather data (Estonian test reference year). Fourth, renovation measures and measure packages were simulated and evaluated against the NZEB renovation target. Fifth, the measured energy use was normalised to account for weather conditions, operational hours, and non-EPB energy uses. The normalisation methods for measured energy use were developed as part of this thesis and are therefore described in detail in Section 3.2.

2.2 Data sources, reference buildings and pre-processing

The case studies cover non-residential buildings, such as office buildings, grocery stores, hardware stores, supermarkets, shopping centres, a school building and a multi-purpose university building. The building samples and individual reference buildings were selected because they had measured energy data, energy audits, implemented or planned improvement measures, design documentation, system descriptions or sub-metering that enabled the methodological analysis. In all publications, the starting point was measured energy use of operational buildings. Depending on the study, the data varied from annual and monthly utility bills to hourly heat, electricity and system-level measurements.

The availability of specific energy data depended on the installed metering devices. Therefore, metered data were complemented with system administration data, in-situ monitoring, building design documentation, energy audit information, and in Publication II with renovation solutions and budgets. In studies using hourly data, cumulative meter readings were transformed into hourly energy use by subtracting consecutive readings. Outliers, errors and missing values were checked before further calculations. Where direct sub-metering was missing, the measured total electricity energy was divided into relevant end uses with energy balance calculations, national standard-use data and information from previous reference studies.

Figure 2: Thesis workflow



The reference buildings described in the following sections and in Table 1 were used to describe typical energy performance challenges and to test new assessment methods. The representative buildings are shown in Figure 3.

The real buildings analysed in the publications are referred to as reference buildings in this thesis, following the terminology used in the original publications. In this context, reference buildings denote measured case buildings used for data collection, model calibration, method development, and demonstration of the proposed energy performance assessment procedures.

Table 1: An overview of the reference buildings used to describe typical energy performance problems and to test new assessment methods in different publications

Building type	**No. of Samples**	**Core Research Focus**	**Publication(s)**
Office	6	Market-based renovation trends and gap compared to climate neutrality target	I
Grocery Stores	22		I
Hardware Stores	11		I
Office	1	Cost-optimal renovation solutions; data-driven baseline generation	II, IV
Secondary School	1	Analytical weather normalisation models for AHU heating coils	III
University Facility	1	Data-driven baseline generation and operational-hours adjustment	IV, V, VI
Retail or Wholesale	7	non-EPB normalisation	VI

2.2.1 Building samples and input data for renovation analyses

2.2.1.1 The market-based renovation analysis Commercial building samples were used to analyse the gap between current renovation practice and major NZEB-level renovation. The sample consisted of six office buildings (Figure 3f), twenty-two grocery stores (Figures 3a and 3b) and eleven hardware stores that were actively in use, constantly maintained, had modern or well-maintained ventilation systems and an acceptable indoor climate. Office buildings often represented mixed-use buildings with some services and trade functions.

The selection criteria were the availability of energy audits and energy improvement measures already implemented or planned, which enabled the preparation of detailed design documentation and budgets. The selected buildings covered a range of heated floor areas, numbers of floors and construction years, enabling analysis of the gap between market-based renovation and NZEB-level renovation across buildings with different characteristics. However, the sample was selected based on data availability, and its statistical representativeness of the Estonian non-residential building stock was not established. The average heated area was 3858 m^2 for hardware stores, 2653 m^2 for grocery stores and 12760 m^2 for office buildings. The construction years ranged from 2001 to 2012 for hardware stores, from 1936 to 2015 for grocery stores and from 1952 to 2012 for office buildings.

In hardware stores, air heating with ventilation supply air was used as a standard solution. In grocery stores, mainly underfloor heating and additionally radiators were used to heat a small number of office and auxiliary rooms. Condenser heat from refrigeration



(a) The supermarket with a floor area below 2500 m^2



(b) The supermarket with a loor area 2500-5000 m^2



(c) The shopping centre with a floor area over 45 000 m^2



(d) The university facility on the TalTech campus



(e) The secondary school building



(f) The office building in publications II and IV

Figure 3: Examples of reference buildings

was used in several cases in the extra heater of an AHU and, in some cases, for DHW or underfloor heating. In office buildings, a radiator heating system was the most common solution. The reference buildings were equipped with a range of ventilation systems, including rotary heat exchangers, systems without heat recovery, variable air volume (VAV) systems, recirculation systems, and natural ventilation in some office buildings. Non-EPB systems included refrigerators, cold rooms, industrial kitchens, outdoor lighting, server rooms, kitchens and control centres.

Delivered energy in the reference buildings was collected from energy invoices based on the main energy meter readings, so specific services were generally not measured. The delivered energy use of hardware stores was taken as the average of 2015-2017, grocery store energy data from 2017-2018 and office building data from 2005 to 2017. Measured electricity data included all types of uses, including server rooms, cold rooms, industrial kitchen equipment, elevators and outdoor lighting. Regarding ISO 52000–1 [28], some calculation procedures allow identification of the partial energy performance for specific services without a dedicated meter. Therefore, total measured electricity energy was divided into the relevant end uses by energy balance calculations.

Lighting and appliances were estimated from the Estonian regulation standard-use specification for internal heat gains. Cooling, refrigeration, fan electricity, electric heating, and other end uses were estimated according to the standard-use specifications in the Estonian regulations [59, 60] and reference data from Swedish [14] and Norwegian studies [37].

For office buildings, reference data was used to evaluate the contribution of the cooling system [37]. These values were based on five reference office buildings, including one reference building from Estonia. The average cooling energy use (space and ventilation supply air cooling) over these office buildings was 18 kWh/m^2 a and the Seasonal Energy Efficiency Ratio (SEER) of 3.5 (for a compressor-type chiller) was taken from the Estonian regulation [59]. With these data and assumptions, the estimated electricity use for cooling was 5.2 kWh/m^2. For the calculation of the energy use of AHU aux, the AHU and the ventilation system were assumed to start 1 h before and stop operating 1 h after the usage time. According to the Estonian regulation, the air flow rate is 2 l/(s $\cdot$ m^2) and the average specific fan power (SFP) for AHU was assumed to be between 2.0 and 2.7 kW/(m^3/s), as these systems were built between 2006 and 2012. This resulted in the annual electricity energy use of the office building AHU fans of 16.0 kWh/m^2, about 24 kWh/m^2 and 32 kWh/m^2 for grocery and hardware stores, respectively.

Office building server room electricity was assumed to be 30% and other extra electricity use to be about 10% of total electricity use. In grocery stores, refrigeration electricity (45% with electric heating and 47% without) was excluded when calculating EPC or primary energy use. Hardware stores were assumed not to have significant additional energy uses; however, the other non-EPB electricity was excluded from the total electricity use. Other non-EPB electricity use was derived as the residual component of the total electricity balance for all building types.

Renovation costs and energy savings were then collected for implemented or suggested measures to compare market-based renovation with the investment needed for major NZEB-level renovation.

2.2.1.2 Cost-optimal renovation to nearly zero energy building level The reference building was an actively used and well-maintained five-storey office building with a heated floor area of 16990 m^2, built in 2008. The office building has a deep foundation and non-load-bearing exterior walls, external floors towards the ambient air and ground, and

roof constructions with mineral wool or EPS insulation. The building had an uncommon shape and a window-to-wall ratio of about 50%. Three elevators were considered, one for each building section. Retail areas and a canteen are located on the first floor, and the other floors are used for offices and health care. Heat supply comes from a local natural gas substation and electricity from the power grid.

Delivered energy of the office building was collected from energy invoices based on the main energy meters and used for the calibration of the simulation model. In 2012-2014, the measured delivered heating energy of this Office building was 104 kWh/m^2 and electricity 126 kWh/m^2 (non-EPB included). Specific end uses were not measured separately but were estimated using calculations and data from previous studies. Domestic cold water use was measured and the DHW share was assumed to be 40%. DHW use was separated from heating energy use and the remaining heating energy use was weather normalised with the degree-day method. The specific electricity for non-EPB use was estimated by further calculations.

Cooling electricity and plug-load electricity were estimated for the server rooms based on the installed cooling capacity of fan coils serving the server rooms. This building has 18 electrical service or server rooms that are cooled by fan coils with cooling capacities ranging from 1 kW to 4 kW. The total installed fan-coil cooling capacity is approximately 61 kW and it was assumed that the servers would operate every day throughout the year (8760 h). Annual cooling energy demand was estimated to be 31 kWh/m^2. A SEER of 3.5 was assumed for the chiller and therefore, the electricity energy was estimated to be 9 kWh/m^2. Outdoor lighting consisted of approximately 25 fluorescent luminaires with a rated power of 58 W each. The annual electricity energy for outdoor lighting was therefore 6.2 MWh (0.36 kWh/m^2). Electricity use of the three lifts was about 13 kWh/m^2, estimated by the study [61].

2.2.2 Case-study data for normalisation methods analysis

The reference buildings described in this section were primarily used to develop and validate the normalisation methods.

2.2.2.1 Air handling unit heat energy weather normalisation The reference building was a 3046 m^2 secondary school building, built in 1980. The building was renovated in 2020 and a new ventilation system was constructed with eleven AHUs with heat recovery. Only one AHU equipped with a rotary heat exchanger was analysed. The AHU served classrooms in one part of the school building and had high-quality metered energy data. The cumulative hourly metered AHU heating-coil energy and fan electricity energy data were obtained from the energy meters from August 2020 to April 2022. Data from 2021 were primarily used in this study. Electricity and heating power were calculated from the differences between consecutive cumulative meter readings. Outliers and errors in electricity power values were corrected using data from the previous hour. Between 8 May and 18 Nov the AHU heating coil operation rate was zero.

2.2.2.2 Weather normalisation methods for post-retrofit baseline generation One reference building was a five-storey university facility building in the TalTech campus with a heated floor area of 10360 m^2, built in 2009. This building was used in Publications IV, V and VI. The total heat loss coefficient of the building envelope was 0.55 W/(m^{2}K) per heated floor area. The window-to-wall ratio was 33% with a window solar factor of 0.4. The air handling units were equipped with heat recovery, heating and cooling coils, while space heating is provided by a radiator system supplied by district heating. The building included

classrooms, auditoriums and offices, as well as non-EPB energy uses such as servers, associated cooling systems and outdoor lighting. The average heating energy use in 2020-2021 (the COVID-19 period), normalised to the Estonian test reference year, was 156 kWh/m^2, and the electricity use was 117 kWh/m^2. Consequently, the operational primary energy use was 335 kWh/m^2 and the EPC class was G (*here corrected*). In Publication VI, the initial EPC calculated from metered energy use was 275 kWh/m^2, which belonged to class F. The difference between the EPCs in these studies is mainly explained by differences in building occupancy during the study periods and by the inclusion of non-EPB energy uses, such as outdoor heating.

Another reference building was the five-storey office building described in detail in Section 2.2.1.2. The heating and electricity energy data was used both for simulation model calibration and for the application analysis of baseline generation. In the period 2020-2021 (COVID-19 years), the average heating energy use, normalised to the Estonian test reference year, was 116 kWh/m^2, and electricity use was 93 kWh/m^2. Therefore, the operational primary energy use was 303 kWh/m^2 and the EPC class was F.

2.2.2.3 Metered energy performance certificate normalisation The metered EPC normalisation study used supermarkets (Figures 3a and 3b), shopping centres (Figure 3c) and a multi-purpose university facility (Figure 3d) because they included refrigeration, tenant loads, servers, outdoor lighting and other energy uses that should not be included in metered EPC assessment.

The study used energy data from main and sub-meters obtained from building owners, monitoring services or a building management system (BMS). The pre-processing procedure illustrated in Figure 4 was determined by the need for adjustment, data granularity and the metering infrastructure.

In the non-EPB energy separation analysis, the wholesale and retail building sample comprised five supermarkets and two shopping centres in Estonia and Finland. All buildings were equipped with refrigeration systems for food storage and included several non-EPB uses, such as external lighting, kitchen equipment, telecommunication rooms, elevators and other auxiliary systems. The main AHUs were equipped with heat recovery, while restaurant kitchens used mechanical extract ventilation. District heating was the predominant heat source, although one supermarket used a heat pump and another was supplied by a local gas station. Buildings had at least annual tenant- or system-level sub-metering that included or directly measured non-EPB services. Most reference buildings used tenant-level metering with monthly readings. One supermarket had annual system-level data, while two buildings provided hourly EPB and non-EPB system-level measurements.

The operational hours adjustment method was applied to normalise the energy use of the multi-purpose university facility with operational hours exceeding typical reference operating schedules. This building is described in detail in Section 2.2.2.2. The university facility was equipped with hourly, system-level metering and required operational hours adjustment. Therefore, pre-processing was first conducted to enable energy use normalisation (see Figure 4). Hourly cumulative energy use data from the main meter and sub-meters were exported from the monitoring system. Hourly energy use was then calculated by subtracting the cumulative value of the previous hour from that of the current hour. Subsequently, the number and proportion of missing hourly records were determined for each month to evaluate data quality. The largest data gap occurred in December, with 74% of hourly values missing; in January, June, July and November, this proportion exceeded 40%. Missing or faulty main-meter readings were excluded, while missing sub-meter readings were replaced with zeros for aggregation. To assess the method's applicability to these

incomplete data, the operational-hours normalisation workflow included validation of reconstructed monthly energy use against measured monthly energy use using CV(RMSE).

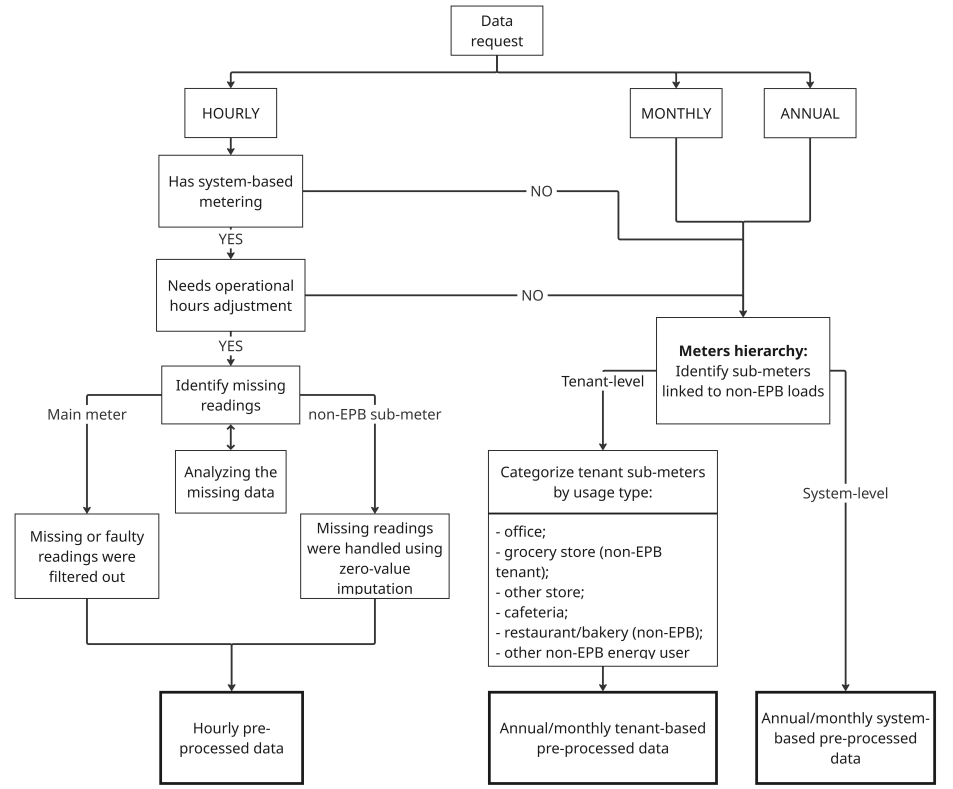


Figure 4: The decision tree and procedure for the pre-processing of raw data from reference buildings

2.3 Market-based renovation and renovation to nearly zero energy building level

2.3.1 Market-based renovation analysis and interviews

For the evaluation of market-based commercial building renovation, the EPC, or primary energy (PE) use, was calculated in accordance with Estonian regulations, as described in more detail in Section 2.6. Measured specific heating and electricity energy use were used, while non-EPB electricity was estimated and subsequently excluded to obtain energy use corresponding to standard conditions. The energy savings of each energy efficiency measure were estimated using the energy-audit calculation methods specified in the Estonian regulations (no longer in force). The energy savings of all measures for each building were combined and subtracted from the energy use before renovation. Finally, the second PE value was calculated to evaluate the level that the buildings would achieve after market-based renovation.

The investment cost of each market-based renovation measure was estimated individually using the Total Concept method. This method focuses on achieving maximum energy saving in the building within the profitability framework set by the building owner, who carries out the investment. The profitability indicator is the IRR set by the building owner. The preconditions were that the investment in the measures had to meet the

requirements of the real estate company, the evaluation of investment and savings had to be reliable, measures had to maintain or improve indoor environmental quality of the building, and savings had to be as large as possible. It was assumed that all these measures would be implemented in the same action package (done all together); thus, the design and construction cost will be lower.

The energy savings were multiplied by energy prices for heating and electricity to calculate annual energy cost savings. Then the payback time was calculated. The measure package was formed by arranging the different energy efficiency measures according to payback time. For comparison, the necessary investment and possible annual energy savings for major renovation to the NZEB level (class C) were estimated. First, the EPC limit value for class C (230 kWh/m^2 for trade and 160 kWh/m^2 for office buildings) was subtracted from the primary energy use after market-based renovation. The result was multiplied by the percentage of energy source and divided by the primary energy factor to obtain annual energy saving in kWh/m^2. Additional investment needed for further renovation was obtained by subtracting the market-based measures investment from the total investment required for major NZEB-level renovation. The energy prices were based on historical energy invoices from the period 2015-2017 and are presented in Table 2. All prices were without value-added tax.

Table 2: Energy prices (without VAT) for grocery stores, hardware stores and office building.

Energy source	**Grocery store**	**Hardware store**	**Office building**
District heating, €/kWh	0.052	0.050	0.050
Natural gas, €/kWh	0.046	0.032	0.034
Electricity, €/kWh	0.072	0.087	0.095

The analysis was based on the IRR calculated for combinations of renovation measures. The three thresholds of 20%, 5% and 2%, used in the IRR analysis, were determined over a 20-year period assuming an inflation rate of 2%. A present value discount rate was applied to calculate the net present value (NPV). The NPV was set to zero over a 20-year period, and the corresponding investment was used to derive the annual savings for a given IRR using Equation 1.

$$0 = \mathrm{NPV} = \sum_{t=1}^{T} \frac{C_t}{(1+\mathrm{IRR}_R)^t} - C_0, \tag{1}$$

where C_t is the annual energy cost in year t, C_0 is the initial investment cost of the measure, and IRR_R is the real internal rate of return calculated with Equation 2, where f is the inflation rate.

$$\mathrm{IRR}_R = \frac{1+\mathrm{IRR}/100}{1+f/100} - 1, \tag{2}$$

As part of the market-based renovation study, face-to-face structured interviews were conducted with building owners to investigate how and why they renovate buildings. In total, six real estate companies, and two representatives from the Estonian Association of Construction Entrepreneurs, representing main contractors, participated in the study. Structured interviews included three main themes:

1. Renovation logic in the market context
2. Motivation to undertake the NZEB-level energy renovation
3. Main problems and solutions

2.3.2 Analysis of cost-optimal renovation to nearly zero energy building level

The aim was to give an overview of the measured energy consumption and analyse energy renovation measures required for NZEB major renovation in office buildings. Several energy-saving measures have already been implemented in the reference office building. However, the improvement of the building automation system, rebuilding of the cooling system, improvement of free cooling in the ventilation and cooling system did not achieve the NZEB level of this building according to the energy audit. Furthermore, a Combined Heat and Power (CHP) plant and a photovoltaic (PV) system had also been installed. A preliminary calculation indicated that these measures would achieve the NZEB renovation level of this building, but this required further detailed investigation.

The renovation measures were selected based on energy audit recommendations, the authors' expertise and measures studied earlier in Publication I. The measures were added to the base model individually, and the saving of each measure was calculated with IDA ICE 4.8. The sequence of measures according to primary energy savings was then composed, and models with measure packages were created by adding each measure one by one to the model. Investment costs and energy cost savings were estimated from project documentation, energy audits and the authors' experience. Energy prices were based on energy invoices in the years 2017-2018 as 0.031 €/kWh and 0.072 €/kWh for natural gas and electricity, respectively.

2.4 Energy simulation and calibration methods

Energy simulation models were developed in IDA Indoor Climate and Energy software. The models were based on building documentation, technical specifications and control strategies of AHUs, information on installed systems, energy audit information and in-situ observations. Where historical performance was analysed, building performance simulations used Estonian historical weather data or the Estonian test reference year. For the supermarket case in Publication VI, the weather file was the ASHRAE IWEC2 weather file for Jyväskylä, Finland.

The purpose of the simulation models differed between publications (Table 3). In Publication II, the office building energy simulation model was used to identify renovation measures and energy savings needed to improve the office building to the NZEB renovation level. In Publication IV, simulation models were composed to generate energy use data for validation of prediction methods before applying them to actual metered data. In Publication V, the output of simulation models was used to validate the operational-hours normalisation method and to identify the most accurate input for operational-hours adjustment. In Publication VI, simulation models were used to validate the normalisation procedures applied to metered energy use: the non-EPB adjustment method was compared with a standard-based simulation model for one representative supermarket, and the operational-hours adjustment was validated using the calibrated model of the multi-purpose university facility.

The calibration method followed the same principle throughout the publications. Energy simulation models were calibrated against the corresponding measured energy use of the reference buildings. Modelling uncertainty was assessed using the Coefficient of Variation of the Root-Mean-Square Error (CV(RMSE)), with (p=0) representing the number of parameters in the simulation model, in accordance with ASHRAE guidelines. The ASHRAE criterion of less than 15% for monthly model calibration was adopted as the primary benchmark for CV(RMSE), and the normalised mean bias error (NMBE) was also reported where relevant with an error threshold of 5%.

In Publication II, the Office building model was built. The base model imitated the real

Table 3: An overview of the simulation models of the reference buildings in different publications

Publication(s)	Building model	Purpose	Calibration accuracy (electricity | heating)
Publication II	Office	analysis of cost-optimal NZEB-level renovation measures	CV(RMSE): 12% | 12%; NMBE: -0.9% | 3.8%
Publication IV	Office	validation of prediction methods (recalibration)	CV(RMSE): 10% | 16%; NMBE: 1.7% | -6.3%
Publications IV and V	University Facility	validation of prediction or operational-hours normalisation method	CV(RMSE): 10.9% | 23.9%; NMBE: 11.1% | 17.5%
Publication VI	University Facility	recalibrated for comparison with the results of the operational-hours normalisation method	CV(RMSE): 4.09% | 9.35%
Publication VI	Supermarket	as-built model with standard use as benchmark	NA

performance of the reference building and had occupancy, appliances, lighting and AHU schedules according to real use. The model was calibrated using the corresponding and normalised monthly energy use data of the reference building for 2014. The calibration results are shown in Table 3. The energy performance simulation under standard conditions was done to calculate the EPC and clarify whether the measures achieve the level of NZEB major renovation.

In Publication IV, the University Facility model was calibrated with monthly metered energy use from 2021, while the Office model was calibrated using weather and metered energy use from 2014. The University Facility model achieved CV(RMSE) values of 10.9% and 23.9%; NMBE 11.1% and 17.5%, for electricity and heating energy use respectively. The Office model achieved CV(RMSE) values of 10% for electricity and 16% for heating, with corresponding NMBE values of 1.7% and -6.3%. Although the heating energy calibration did not achieve the ASHRAE threshold (partly influenced by COVID-19), the models were considered appropriate for case study analysis and method evaluation. The output of the simulation model was used for the validation that is described in detail in Section 2.5.2.1.

In Publication V, the calibrated model of the University Facility was reused for the validation of operational-hours adjustment (described in detail in Section 2.5.3.2).

In Publication VI, the University Facility model was recalibrated for the purposes of this analysis using metered energy data, achieving CV(RMSE) values of 4.09% for electricity and 9.35% for heating energy use. These results meet the ASHRAE threshold of less than 15% for computer model validation. Furthermore, the standard (STD) simulation model was derived from the calibrated model where the lighting schedules and appliance power load and schedules were set according to standard values of educational and office buildings (standard profile excludes the base load). The outputs of the simulation models were used to compare the results and validate the operational hours adjustment method applied to the metered data.

The Supermarket model was based on the building design documentation, technical specifications and control strategies of the AHUs, information on the installed systems, and in-situ observations. The simulation represents an as-built standard model, excluding

non-EPB energy use and dehumidification.

After calibration, standard models were derived from calibrated models by setting mostly lighting schedules, appliance schedules and power loads, and where needed, also occupancy and ventilation schedules according to the Estonian national calculation methodology. In the office-building renovation case (Publication II), the standard-condition simulation was used to calculate the EPC and clarify whether renovation measures achieved the NZEB renovation level. In the operational-hours studies, standard models were used as the benchmark against which the normalised metered energy use (Publication VI) and the normalised simulation model energy use (Publication V) were compared.

2.5 Methodological workflow for normalisation method development

2.5.1 Air handling unit heat energy weather normalisation

Two weather normalisation calculation methods were compared for AHU heating coil energy consumption in a school building equipped with an AHU with a rotor heat exchanger: (i) an analytical model for weather normalisation with mean temperature (MT); (ii) the HDD method. The normalisation methods were developed as part of this thesis and are therefore described in detail in Section 3.2.1. Metered AHU electricity and heating energy use data, together with the hourly outdoor temperature and calculated AHU heating demand, were used as input for the analysis and modelling.

The real capacity calculation model that was calibrated with hourly measured ventilation heating and electricity energy data was used to imitate the actual AHU heater energy need (Equation 4). The model takes hourly outdoor temperature data T_{out} and AHU parameters (Table 4), and calculates the heating coil heat output (power) in kW for every hour for one year. The fan temperature rise was set to 0 K.

The metered data showed that the electricity energy use varied over time. Therefore, the operation rate of the AHU heating coil was generated from electricity power using Equation 3, where τ_i is the operation rate in a specific hour, $\Phi_{el,i}$ is electricity power (kW) in a specific hour and $\Phi_{el,max}$ is the maximum electricity power (kW) during the calculation period.

$$\tau_i = \sqrt[3]{\frac{\Phi_{el,i}}{\Phi_{el,max}}} \tag{3}$$

$$\Phi_v = \rho \cdot c \cdot \Delta T_h \cdot q_v \cdot \tau_i \tag{4}$$

where ρ is the density of air (1.2 kg/m^3), c is the specific heat capacity of air (1.006 kJ/(kg·K)), q_v is the air flow rate, m^3/s, multiplied by the AHU operation rate τ_i; ΔT_h is the temperature difference that the heater should cover:

$$\Delta T_h = \max\left(T_{supply} - T_{after,hx}, 0\right) \tag{5}$$

where T_{supply} is the supply air setpoint temperature in °C and was considered constant; $T_{after,hx}$ is the air temperature in °C after the heat exchanger and is calculated as:

$$T_{after,hx} = \eta_{hx,lim} \cdot (T_{extract} - T_{out}) + T_{out} \tag{6}$$

where $T_{extract}$ is the extract temperature, which is equal to room temperature in °C; T_{out} is the outdoor temperature in °C; and $\eta_{hx,lim}$ is calculated as:

$$\eta_{hx,lim} = \frac{T_{extract} - T_{exhaust}}{T_{extract} - T_{out}} \tag{7}$$

where $T_{exhaust}$ is the temperature in ℃ after the heat exchanger that is limited and was calculated as:

$$T_{exhaust} = \max\left(T_{extract} - \eta_{hx,const} \cdot (T_{extract} - T_{out}), T_{exhaust,lim}\right) \quad (8)$$

However, in this case, as the rotor did not significantly increase heating energy use despite outdoor temperatures below -30 °C, $\eta_{hx,lim}$ was always $\eta_{hx,const}$.

The heat recovery parameters of the AHU were detected by parameter optimisation by minimising the CV(RMSE) between the measured AHU heating-coil heat output and that calculated with Equation 4 using real outdoor temperature (separately for January, February, March, November, December). The optimisation was in limits: supply air temperature 16-21 °C, extract air temperature 22-24 °C, and heat exchanger efficiency 0.75-0.9. The final parameter values were obtained by averaging the optimised parameters across these months (Table 4).

Table 4: AHU parameters

Parameter	**Abbreviation**	**Value**
Minimum exhaust air temperature, °C	T_{exhaust}	-30
Extract air temperature, °C	T_{extract}	21.75
Ventilation air flow rate, l/s	q_{v}	4749
Supply air temperature, °C	T_{supply}	20.26
Heat recovery efficiency	η_{hx}	0.809

HDD weather normalisation was done by multiplying the measured AHU heating energy consumption by the ratio of test reference year HDDs and real-year HDDs (Equation 9).

$$Q_{v,\text{HDD,corrected}} = Q_v \cdot \frac{HDD_{\text{TRY}}}{HDD_{\text{Real}}} \quad (9)$$

2.5.2 Weather normalisation methods for post-retrofit baseline generation

The study used hourly heating and electricity data obtained from a university facility and an office building to develop simulation models and predict baseline building energy use at monthly resolution. In summary, the validation of two approaches was carried out with simulation model data. Thereupon, the actual metered energy data from 2017 to 2022 were used for the application analysis of the methods.

The degree-day method uses monthly degree-days and energy use data. Monthly degree days are calculated from hourly average outdoor temperature data over the measurement period, using a predefined base temperature for a specific building. The machine learning method uses hourly weather and energy use data to produce long-term baseline energy use prediction. The normalisation methods were developed as part of this thesis and are therefore described in detail in Section 3.2.2.

The weather dataset included hourly outdoor air dry-bulb temperature (°C), relative humidity (%), wind speed (m/s) and direction from the Tallinn-Harku weather station. Additionally, solar direct radiation to normal and diffuse radiation on a horizontal surface (both in W/m^2) were obtained from the Tartu-Tõravere weather station.

As buildings' energy use is significantly impacted by outdoor conditions, the correlation between heating energy use and weather conditions was analysed. The daily heating energy use of two reference buildings correlates with outdoor temperature and direct solar radiation to normal. In the university facility, daily electricity energy use appears unaffected by weather conditions. However, in the office building, a correlation is evident – as outdoor temperature rises, electricity energy use increases, particularly in the 10–15 °C range.

2.5.2.1 Performance and uncertainty of baseline prediction models The validation of the prediction methods was carried out using simulation model data. By utilising simulation models' output during the 2017–2019 period for training, the models were derived with two prediction methods. Then the energy use was predicted for 2020–2021. Subsequently, these predictions were compared against the simulation models' output for the same period. The simulation models were used to collect data on energy use within predetermined boundary conditions, thereby eliminating anomalies caused by external factors like COVID-19 and the energy crisis in 2020–2021. This focused on the performance of the predicting methods and their uncertainties.

Thereafter, the same workflow was applied to actual metered energy use data. Metered energy use data from both buildings were collected for the period 2017–2022 from the office building (RB2) and for the period 2020–2022 from the university facility (RB1). These data were used to analyse the application of the prediction models in a real situation. By utilising metered energy use data from RB2 during the 2017–2018 period for training, the models were derived with the prediction methods. Then the energy use was predicted for 2019. Subsequently, these predictions were compared against the metered energy use data for the same year. External factors (such as COVID-19 and the energy crisis) significantly influenced the energy use in the 2020–2022 period. Therefore, in addition to pre-COVID analysis, the same procedure was done for the COVID-19 period with RB1 and RB2. The training period was from July 2020 to July 2021 and the prediction period was from July 2021 to July 2022. The prediction model's performance analysis is outlined in Figure 5.

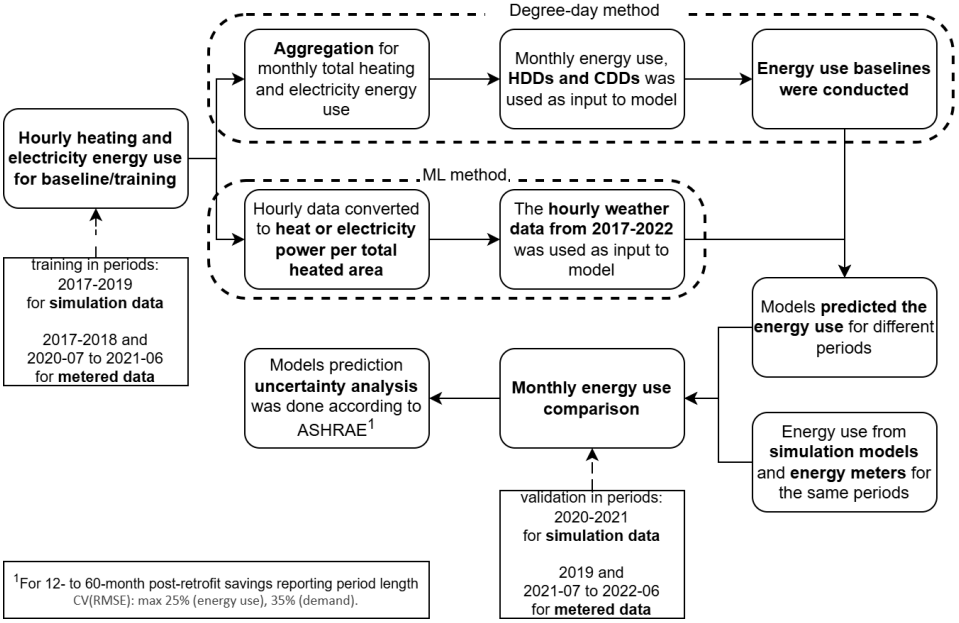


Figure 5: Models' inputs description and uncertainty analysis of the prediction models for both data gathered from simulation models and energy meters in 2017–2022.

The uncertainty analysis and validation procedure followed the same workflow for both validation and application phases. Model performance was evaluated by comparing predicted energy use with simulated or metered reference data and quantifying the deviation using statistical indicators. The main evaluation metric was the CV(RMSE), calculated over the analysis period to assess prediction accuracy. This approach enables consistent evaluation of model reliability and ensures compliance with Guideline 14 [62] criteria for baseline

prediction and energy savings assessment. According to ASHRAE Guideline 14, the maximum allowable CV(RMSE) for a post-retrofit savings period of 12–60 months is 25%. The additional metrics were the coefficient of determination (R^2), NMBE, Root-Mean-Square Error (RMSE) and monthly percentage error.

2.5.3 Metered energy performance certificate normalisation workflow

Focusing on the applicability within the European context, the analysis of metered EPC normalisation workflow (flowchart in Appendix A) was based on the EPBD and the Estonian national regulatory framework, with particular emphasis on the EPC derived from metered energy use. In addition to the technical systems related to IEQ, the Estonian methodology accounts for energy use from appliances. All other services (non-EPB), like process energy, refrigeration, servers, catering, etc., should be excluded. However, the EPBD does not prescribe how to exclude non-EPB services when not separately metered and how to adjust operational hours. Therefore, there is a need for a clear procedure for building energy performance assessment.

After data pre-processing (described in detail in Section 2.2.2.3), the EPC assessment procedure was followed with adjustment of non-EPB energy use with different methods for hourly and monthly data. The operational hours adjustment continued by first defining the usage profile and thereafter conducting the normalisation.

Agreement between reconstructed and measured monthly energy use was assessed using CV(RMSE) as recommended by ASHRAE Guideline 14-2023 [62], with n representing the number of months evaluated and $p = 0$.

Finally, the energy simulation models were used to validate the normalisation procedures. The adjustment method for non-EPB energy use was compared with a standard-based simulation model for one representative supermarket. The validation of the operational-hours adjustment was conducted using a calibrated simulation model of a multi-purpose university facility building.

2.5.3.1 Separation of energy use outside the energy performance of buildings assessment boundary

The method enables adjustment for non-EPB energy use by using data from the main meter and tenants' electricity meters. The performance of the new method is demonstrated through case studies that report calculations based on monthly or annual system-level and tenant-level metered energy use data. This method enables the partial removal of non-EPB energy use, both by deducting energy from the main meter and by replacing it with standard use data, thereby normalising the dataset to EPB services prior to performance evaluation.

In buildings where non-EPB services are measured through dedicated system-level sub-meters, the main meter provides total delivered energy and the individual sub-meters quantify the consumption of specific technical systems. Where such systems fall outside the EPBD definition of energy performance of buildings, for example refrigeration units, server rooms or catering equipment, their measured energy use can be subtracted from the total delivered energy before EPC calculation. However, where non-EPB services are embedded within tenant-level electricity measurements, direct subtraction of the tenant meter would remove not only process-related loads but also electricity uses consistent with typical EPB assumptions, such as appliances and lighting. To address this, a replacement-based normalisation procedure was introduced and described in detail in Section 3.2.4.1.

2.5.3.2 Operational-hours adjustment

The operational-hours adjustment was developed and validated first in Publication V. A calibrated simulation model of the reference

building was developed and used to construct four modelling scenarios for operational-hours adjustment: (i) a REAL model that reflects a building with extended operational hours, (ii) REAL model + base load, where the average base load of 2.7 W/m^2 was added outside of operating hours, (iii) a Standard model that represents a building defined according to Estonian regulations [59, 60], and (iv) Standard model + base load, which is the same as (iii), but outside operational hours, the power load is 2.7 W/m^2.

Furthermore, two methods for defining the operational hours were tested: the user schedule, indicating when the building is occupied, and the AHU schedule, indicating when the AHU is operating.

In Publication VI, the same reference building and its metered energy use were further analysed to evaluate the operational-hours adjustment method as the building represented a multi-purpose university building with operational hours exceeding typical reference operating schedules.

2.6 Regulatory constraints and Estonian energy performance certificate assessment framework

The regulatory basis of the thesis is the EPBD and the Estonian national energy performance methodology. The Estonian methodology calculates the EPC as annual weighted specific delivered energy use per heated floor area. In accordance with the Estonian national methodology, the EPC is determined using Equation 10 and metered energy data for each building system and energy carrier. Space heating and ventilation heating are separated from total heating energy use to apply weather normalisation using HDD. After adjustments and weather normalisation, the energy use of each system is normalised to heated floor area and aggregated. The total energy use is then multiplied by primary energy conversion factors. The publications used factors of 0.65 for efficient district heating, 1.0 for natural gas and fuel oil, and 2.0 for electricity. In Estonia, EPC benchmarks are fixed limits defined by building type, and the operational EPC calculated by an assessor must be reproducible and is valid for up to ten years.

$$E_{\mathrm{we}} = \sum_j \left(E_{\mathrm{we,adj,wnorm,H,cr},j} \cdot \mathrm{PE_{cr}}\right) + \sum_j \left(E_{\mathrm{we,DHW,cr},j} \cdot \mathrm{PE_{cr}}\right) + E_{\mathrm{we,adj,el}} \cdot \mathrm{PE_{el}} \qquad (10)$$

where E_{we} is the EPC value as annual weighted specific use of delivered energy in kWh/m^2 per heated floor area, $E_{\mathrm{we,adj,wnorm,H,cr},j}$ is weather normalised delivered energy for space and ventilation heating per energy carrier, $E_{\mathrm{we,DHW,cr},j}$ is delivered energy for domestic hot water per energy carrier, $E_{\mathrm{we,adj,el}}$ is adjusted delivered electricity energy, PE_{cr} is the primary energy conversion factor per carrier.

The main regulatory constraint is the assessment boundary. In addition to technical systems related to indoor environmental quality, the Estonian methodology accounts for energy use from appliances. The following categories were considered as non-EPB services in the normalisation study: grocery store refrigeration and chillers, kitchen equipment, restaurants with high-power kitchens, outdoor lighting, marketing screens, car washes, telecommunication rooms, elevators, server room electricity and chillers serving servers, ice rinks or other systems not intended for HVAC.

The national methodology also defines standard operational hours according to the European Standard EN 16798-1 [63]. In the publications, the standard operational hours were 8:00-16:00 for educational buildings, 7:00-18:00 for offices and 7:00-21:00 for wholesale buildings. Ventilation is assumed to operate one hour before and after these

periods. Outside operational hours, the power loads of appliances and lighting are zero in standard calculations.

In this thesis, the regulatory framework is used as the reference for all methods. The EPC target for major renovation is class C in the Estonian regulation applied in the publications. The purpose of normalisation is not to remove real performance differences but to make measured energy use correspond to the EPB scope, typical operational hours and reference weather required by the assessment framework. This is necessary if metered EPCs are to be used for MEPS compliance and for fair comparison of non-residential buildings.

3 Results

3.1 Energy use and renovation practice in Estonia

3.1.1 Energy performance in buildings before market-based renovation

It is evident that the measured energy performance of commercial buildings is strongly influenced by both technical system performance and energy uses outside the EPBD assessment boundary. Analyses were carried out for six office buildings, twenty-two grocery stores and eleven hardware stores. According to previous studies, estimated non-EPB electricity represented approximately 20-30% of electricity use in hardware stores, up to 80% in grocery stores when refrigeration and other process loads were included, and 50-70% in office buildings. The dominant non-EPB uses were refrigeration, server rooms, kitchens, elevators, outdoor lighting and other tenant-related loads.

After the estimated non-EPB electricity use had been excluded, only a limited number of buildings approached the class C level corresponding to the NZEB renovation target in Estonia, shown by the horizontal axis in Figure 6. Two hardware stores were close to class C, with PE values of 214 and 231 kWh/m^{2}a. In grocery stores, only a few buildings approached the target after refrigeration electricity had been excluded, while the two best-performing office buildings still had PE values of approximately 207 kWh/m^{2}a, approximately 40 kWh/m^{2}a above the class C limit.

3.1.2 Market-based commercial building renovation in Estonia

The analysed market-based renovation practice improved energy performance only marginally compared with the NZEB target. The measures implemented or suggested in energy audits were mainly those with short payback times and low investment costs, such as building automation, remote monitoring, lighting replacement, demand-controlled ventilation, HVAC control improvements and selected system upgrades. Although these measures were technically useful, they did not reach class C in most buildings (Figure 6).

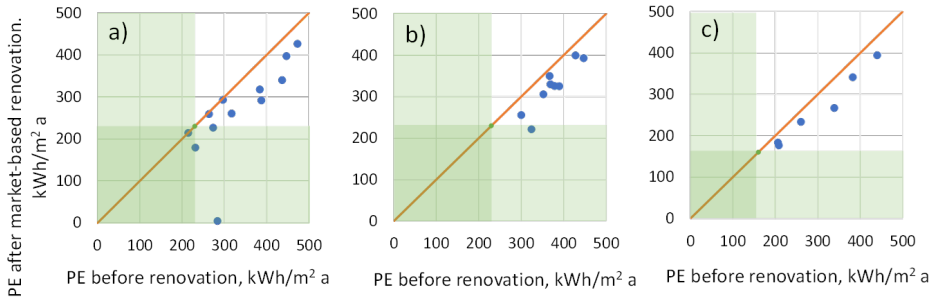


Figure 6: The primary energy (PE) use before and after market-based renovation of hardware stores (a), grocery stores (b) and office buildings (c). The green area is the boundary of C-class and in grocery stores, 15 buildings are outside of graph.

In office buildings, PE use changed only slightly, and the sample did not reach the NZEB renovation level. Two of the analysed buildings stay in class D and one in class E. Only in two buildings, the EPC class increased to a one step higher class and one of them was on the limit to reach two steps. PE use decreased by 45 kWh/m^2 and 70 kWh/m^2 in these two buildings, respectively.

In hardware stores, the improvement was more visible, but approximately 65% still failed to reach class C. Under market-based renovation, three buildings achieved class C

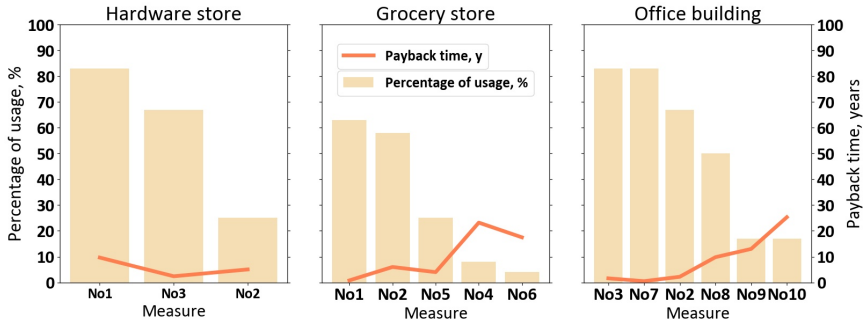


Figure 7: The usage of measures (in Table 5) compared with the payback time of renovation in hardware stores, grocery stores and office buildings

or B with PE values of 180–225 kWh/m^2. In grocery stores, only one building improved from class E to class C after renovation with 222 kWh/m$_2$, while most buildings remained in classes E-H.

The measures with the investment per heated floor area presented in Table 5 include all of those implemented or suggested in energy audits, i.e., representing the level of the market-based renovation. These measures have been selected because of good payback time, as shown in Figure 7. Some differences in investments (e.g., measure No 3) are derived from variation in average heated area. However, bigger changes come from the extent of installations, which vary in each building.

In the hardware store, only three renovation measures were considered. The modernisation of building automation (No 1) and changing the ventilation system to demand-controlled ventilation (DCV) (No 3) were the main measures used in the hardware store. Measure No 1 was the most used, because it needs less effort and remote monitoring achieves good energy efficiency with low investment.

Regarding the cost effectiveness, in the grocery store, the modernisation of building automatics (No 1) and better lighting (No 2) have had the best payback times and are therefore often recommended to companies. Also, changing the heating or ventilation system (No 5) has a good payback time, but the majority of these buildings already have HVAC systems that need no replacement. Refrigeration renovation (No 4) was mainly suggested because of the old system and measure No 6 for one grocery store because there is no insulation on the outer wall of the building.

In the office building (Figure 7), the most recommended measures are DCV or ventilation automation renovation (No 3), improvement of HVAC system control (No 7), and improving the lighting from fluorescent to LED lighting (No 2). Other measures were used only, at a special need, e.g., in case of an old system, the improvement of which was cost-optimal, the renovation of the HVAC system and the system balancing was done. The installation of the solar protection film was proposed in case of complaints about glare or overheating.

As an additional method, PV panels and CHP plants were used for on-site energy generation, however rarely because of big investment needs. The maximum payback time of PV panels installation for grocery stores was about 12.9 years. One case for the office building was 14 years. In energy savings, this was a good solution for grocery stores because the average decrease of EPC was as high as 128 kWh/m^2 year. On the other hand, none of these companies used these solutions because of the longer payback time. Further, buildings with steel profiled sheet roofs (as usual for trade buildings) would need structural reinforcement of the roof to install PV panels.

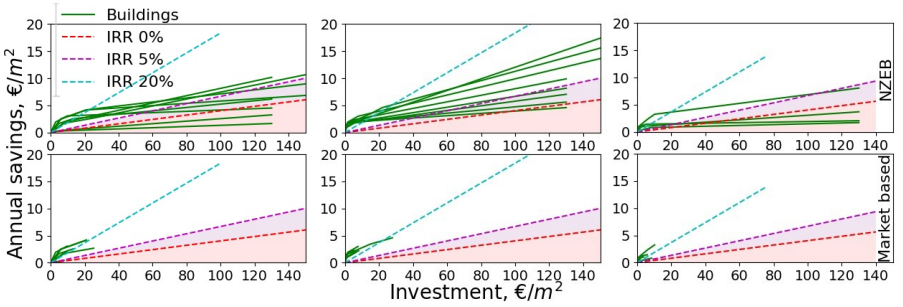
Table 5: Energy efficiency improvement measures implemented in commercial buildings (investment cost of energy audits in 2015-2019)

No	Measure	Description	Building	Investment, €/m^2
1	Building automatics	Renovation of building automatics, distance monitoring of HVAC systems	GS & HS	1.4 and 12
2	Better lighting	Fluorescent lighting replaced with LED, movement sensors installation. In the office building, only in the corridor.	GS, HS and OB	5.7, 19 and 1.3
3	DCV or ventilation automatics	Installing the CO_2 sensors in the room, connecting them with AHU automatics; for the office building, also night setback and heat exchanger cooling function	HS and OB	5.3 and 0.6
4	Refrigeration renovation	Replacing the refrigeration and designing the condenser heat utilisation in the heating system	GS	31
5	Larger renovation of HVAC systems	Changing the local heating source or ventilation system	GS	30
6	Building wall insulation	Installing thicker or more efficient insulation	GS	27
7	Improvement of HVAC control	Changing the control characteristics and automatics of HVAC systems	OB	0.4
8	Modernisation of HVAC	Renovation of the AHU fans, heating/cooling coil, heat exchanger, or heating/cooling system and heating/ventilation system balancing	OB	0.4
9	Modernisation of heat supply system	Renovation of the heat supply system	OB	4.5
10	Installation of solar protection film	Installing solar window films	OB	6.7

Note: GS = grocery store; HS = hardware store; OB = office building.

3.1.3 Acceptable renovation costs for real estate companies in Estonia

The common renovation cost accepted in practice was approximately 10 €/m^2. In contrast, renovation packages needed to reach the NZEB renovation level were estimated to require approximately 130-150 €/m^2. Figure 8 shows the gap between the objective to achieve major NZEB-level renovation and the actual performance of the market today. The comparison is based on the IRR calculated from the combination of renovation measures. The bottom part of the graphic shows the IRR of market-based measures and the graph on the top shows the IRR to achieve the NZEB renovation level. Market-based renovation packages typically had an IRR around 20% (in some specific cases, 7% was also acceptable when a building clearly needed renovation), whereas NZEB-level packages often had an IRR below 7% in many office and hardware store cases, and sometimes even below 0%. The interviews confirmed that landlords normally preferred payback times below 10 years, while NZEB-level renovation was associated with payback times of 20-40 years.



(a) Hardware store *(b) Grocery store* *(c) Office building*

Figure 8: The internal rate of return (IRR) for hardware (a), grocery (b) store and office (c) building renovation measures

3.1.4 Results of interviews with real estate companies

The statistical and interview results explain why technically feasible renovation measures were not implemented. Tenants usually paid the utility bills, whereas landlords made decisions on renovation investments. If rent could not be increased after renovation, the landlord had limited motivation to invest, because the direct energy cost benefit was received mainly by the tenant. Tenants, in turn, were reluctant to co-finance renovation.

According to estimates from Statistics Estonia for 1999-2009, the average annual rental price over a ten-year period was 98 €/m^2 in Tallinn office buildings and 129 €/m^2 in trade buildings, based on lease transactions intermediated by real estate companies in Estonia. The annual energy cost was 9-24 €/m^2 in office buildings and 10-28 €/m^2 in trade buildings. Therefore, the average energy cost, 11 €/m^2 in offices and 17 €/m^2 in hardware stores, represented about 10-12% of the sum of rental and energy costs (Figure 9).

Market-based renovation reduced the average energy cost by only about 1-3% in office buildings and hardware stores, whereas NZEB renovation reduced it by 3-4%. In grocery stores, the corresponding reductions were 4% and 8%, respectively. This benefit was considered marginal because it had to be shared between the landlord and the tenant.

Nevertheless, there are some positive aspects in the market. Investors that are not landlords are more likely to invest in real estate that has a green certificate. Furthermore, from a tenant's perspective, some foreign companies have green policies, so they are interested in energy performance and will encourage the landlord to improve the building. Another driver is the ageing of technical systems, as tenant complaints about poor indoor climate eventually force renovation.

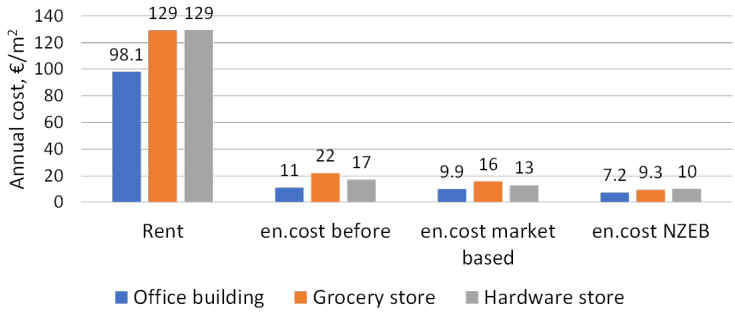


Figure 9: Comparison of annual rent and energy cost for three reference buildings.

The main barriers were considered to be the long payback time of renovation and the lack of tenant demand for energy renovation. Interviewees pointed out the need for new taxes that would raise energy costs and stimulate renovation by building owners. New taxes should be accompanied by incentives for energy-efficient renovation, as no renovation grants or financial incentives for commercial buildings currently exist in Estonia (for example, incentives for building monitoring and energy audits). One proposed solution was to require building owners to prove the energy performance of buildings every 20 years. Real estate companies preferred earlier information about regulatory changes, more stable EPC class boundaries and primary energy factors, and more detailed energy audits. Interviewees proposed developing detailed renovation measure packages to improve certainty regarding energy performance improvement and reduce investment risk. In the case of government grants, companies would probably accept longer payback periods of 12–15 years.

3.1.5 Cost-optimal solutions for nearly zero energy building level renovation

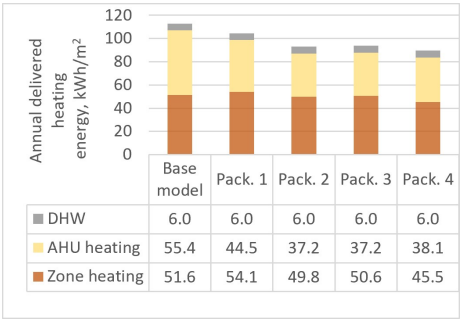
The measured delivered energy use of a five-storey office building was 104 kWh/m^{2}a for heating and 126 kWh/m^{2}a for electricity, including non-EPB electricity use. After modelling the building under actual operating conditions, heating and electricity use were 113 and 75 kWh/m^{2}a, respectively, resulting in a PE use of 263 kWh/m^{2}a. Under standard-use conditions, heating and electricity use decreased to 89 and 56 kWh/m^{2}a, respectively, corresponding to a PE use of 201 kWh/m^{2}a and an EPC class D.

Analysis of individual renovation measures showed that lighting replacement was the most cost-optimal measure (Table 7). Replacing fluorescent lighting with LED reduced PE by 18.6 kWh/m^{2}a, had the lowest investment per saved PE, 0.47 EUR/kWh, and had the shortest payback time, 12.5 years. Other measures produced useful savings but were less attractive economically. Improving AHU fans or heat exchanger efficiency required replacement of the whole AHU, approximately 20 EUR/m^2, and the combined AHU improvement payback time was about 26 years. Measures such as solar protection film and improvement of the free cooling function had lower value in this case and were not included in the later package analysis. A 69 kW photovoltaic system was treated as an additional measure needed to reach the NZEB renovation level.

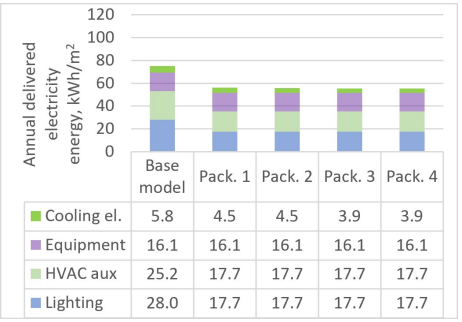
The package analysis showed that NZEB-level renovation was technically achievable, but only with combinations of measures and long payback times (Figure 10 and Table 6). Package 1 included measures 1-4 and reduced electricity and heating use by 19 and 8.4 kWh/m^{2}a, respectively. The resulting standard-use PE was 173 kWh/m^{2}a, still class D. Adding canteen AHU control with CO_2 sensors in Package 2 reduced heating by a further 7.2 kWh/m^{2}a and gave PE of 165 kWh/m^{2}a, close to the NZEB renovation level. Package 3 added window replacement and reduced heating by another 3.5 kWh/m^{2}a, reaching

160 kWh/m^{2}a, the class C threshold (with PV). Package 4 used night setback of indoor temperature in addition to previous measures and saved 4.3 kWh/m^{2}a of heating energy, giving a PE result around 163 kWh/m^{2}a without PV that is close to the NZEB renovation level. Nevertheless, to achieve the NZEB renovation level, the installation of a PV system is essential.

Half of the individual measures had payback times above 40 years, and some reached more than 60 years. Combining measures reduced the payback time, but the resulting 30-34 year package payback times were still outside the approximately 10-year payback expectation identified in market-based renovation analysis (Publication I).



(a) Annual delivered real heating energy for the base model and models with different renovation packages



(b) Annual delivered real electricity energy for the base model and models with different renovation packages

Figure 10: Results of different renovation packages

Table 6: Main renovation package results in the office-building case study.

Case	Energy performance result	Economic result – payback time
Base building, standard use	89 kWh/m^{2}a heating, 56 kWh/m^{2}a electricity and 201 kWh/m^{2}a PE; EPC class D.	Existing condition.
Package 1	PE reduced to 173 kWh/m^{2}a; still class D.	32 years
Package 2	PE reduced to 165 kWh/m^{2}a; close to NZEB renovation level.	30 years
Package 3	PE reduced to 160 kWh/m^{2}a; reaches class C threshold.	34 years
Package 4	PE around 163 kWh/m^{2}a without PV; near NZEB renovation level.	32 years

3.2 Development and application of energy performance of buildings assessment methods

The normalisation methods developed in Publications III– VI address the fact that measured energy use may not correspond to the standard EPB scope used in EPC assessment. The studies considered three main normalisation problems: weather normalisation, non-EPB energy use and operational hours. Additional aspects such as deviations of indoor temperature and DHW use were not analysed in detail, because they usually have a smaller impact on total energy use in non-residential buildings. Through all the papers, the methods are aimed to be as simple as possible and require a minimum number of input parameters

Table 7: Energy renovation measures and cost-effectiveness indicators

No	Measure description	Parameters		Delivered energy savings, kWh/m^2		Annual cost savings, €/m^2		Investment, €/m^2	Saved PE, kWh/m^2	€ per saved PE kWh	Payback time
		Base model	After	Electricity	Heating	Electricity	Heating				
1	Improving the lighting	In trade area 12 W/m^2, office 10 W/m^2	In trade area 12 W/m^2, in office 6 W/m^2	11.37	-4.45	0.82	-0.14	8.52	18.3	0.47	12.5
2	Improvement of AHU fans SFP	SFP = 1.098-1.93 kW/(m^3/s)	SFP = 1-1.7 kW/(m^3/s)	6.25	0.01	0.45	0.00	20.0	12.5	1.6	44.4
3	Improvement of AHU heat exchanger	Efficiency: rotary heat exchanger 70%; coil heat exchanger 40%	Efficiency: rotary heat exchanger 80%; coil heat exchanger 60%	0.08	9.74	0.01	0.30	20.0	9.91	2.02	65.0
4	Adding the cooling effect to AHU heat exchanger	Heat exchanger is not working between 14 May and 31 August	Heat exchanger is working all the time	0.11	6.92	0.01	0.21	4.0	7.13	0.56	18.0
5	Change of canteen's AHU ventilation control	CAV	VAV with CO_2 control and setpoints min 700, max 800	1.50	4.15	0.11	0.13	4.0	7.16	0.56	16.9
6	Changing the windows from 2-layer to 3-layer windows with better sun protection	Pilkington Suncool 66/33 (6C(66)-15Ar-4): g0.36, T0.33, Tvis0.66, U1.1	Pilkington Suncool 40/22 (6C(40)-15Ar-4-15Ar-S(3)4): g0.2, T0.17, Tvis0.36, U0.6	0.75	3.84	0.05	0.12	12.0	5.34	2.24	69.3
7	Night setback of indoor temperature	Constant 21 °C	6-20:00 set to 21 °C; other time set to 19 °C	0.20	4.78	0.01	0.15	0.06	5.18	0.01	0.39
8	Sun protection film improving the windows shading	Shading parameters: g0.36, T0.33	Shading parameters: g0.20, T0.13	0.73	-2.41	0.05	-0.07	6.33	-0.94	-6.70	NA
9	Improvement of free cooling function [1]	Tamb $<$ 11 °C, Tsupply = 18 °C; Tamb $>$ 11 °C, Tsupply = 16 °C	Tamb $<$ 15 °C, Tsupply = 18 °C; Tamb $>$ 15 °C, Tsupply = 16 °C	-0.33	-1.14	-0.02	-0.04	0.06	-1.80	-0.04	NA
10	PV panel installation	No PV system	Installation of 230 panels with a system power of 69 kW	3.28	0	0.24	0.00	5.62	6.6	0.86	23.8

[1] *The setpoint of supply air temperature (Tsupply) was adjusted by ambient temperature (Tamb)*

from building energy meters and stakeholders. The rationale for this is the current low quality of available data.

This section first presents the methodological development of the normalisation procedures and then demonstrates their application in reference buildings.

3.2.1 Developed methods for air handling unit heat energy weather normalisation

The AHU heating coil power for the test reference year climate was calculated on an hourly basis using equations described in Section 2.5.1. The results were aggregated into daily, weekly, monthly and annual values, and subsequently compared with the results obtained using the two normalisation methods: the mean temperature (MT) and HDD methods.

3.2.1.1 Heating degree day (HDD) method The heating degree-day method used HDDs that were calculated using daily average outdoor temperatures derived from hourly outdoor temperature data for both the test reference year (TRY) and the real year. In this analysis, the hourly data was filtered using two approaches: (i) including all 24-hour outdoor temperature data (excluding May-November), and (ii) including only outdoor temperature data during periods when the operation rate (fan speed) exceeded 54%. The latter approach, which considers only periods with AHU operation above 54%, provided higher accuracy. The base temperature was identified with a change-point method, defined as the intersection of the linear regression line of heating energy use with the outdoor temperature axis. The best-fitting base temperature of 14.4 °C was determined using cleaned data, considering only periods with a minimum fan speed of 54%.

3.2.1.2 Analytical model for weather normalisation The analytical weather normalisation model was based on the difference in ventilation air heat capacity between the real and Test Reference Year (TRY) climates ($\Delta\Phi_{\mathrm{TRY,Real}}$), as expressed in Equation 12. The corrected ventilation air heat capacity, $\Phi_{h,\mathrm{corrected}}$, was calculated with Equation 11. The outdoor temperature was limited by the base temperature, which is the outdoor temperature at which no heating is needed.

$$\Phi_{h,\mathrm{corrected}} = \left(\Phi_{h,\mathrm{real}} + \Delta\Phi_{h,\mathrm{TRY,real}}\right)^{+} \tag{11}$$

where

$$\Delta\Phi_{\mathrm{TRY,Real}} = \rho \cdot c \cdot q_v \cdot \tau_i \cdot \left(T_{h,\mathrm{real}} - T_{h,\mathrm{TRY}}\right) \tag{12}$$

$$T_{h,\mathrm{Real}} = T_{\mathrm{out,real}} + \min\left(T_{\mathrm{extract}} - T_{\mathrm{exhaust,lim}}\,;\, \eta_{\mathrm{hx}} \cdot \left(T_{\mathrm{extract}} - T_{\mathrm{out,real}}\right)\right) \tag{13}$$

$$T_{h,\mathrm{TRY}} = T_{\mathrm{out,TRY}} + \min\left(T_{\mathrm{extract}} - T_{\mathrm{exhaust,lim}}\,;\, \eta_{\mathrm{hx}} \cdot \left(T_{\mathrm{extract}} - T_{\mathrm{out,TRY}}\right)\right) \tag{14}$$

The heat recovery parameters of the AHU in Table 8 were detected by parameter optimisation by minimising the CV(RMSE) between real metered heat output and AHU heating coil heat output calculated using real outdoor temperature. The method is detailed in Section 2.5.1.

In the original hourly formulation, the analytical model calculates the ventilation heating capacity using the AHU operation rate derived from measured fan electricity power. When the method was applied to daily, weekly or monthly aggregated data, the operation rate was summed over the corresponding aggregation period. Therefore, the aggregated operation rate represented the equivalent AHU operating time during the period, including partial-load operation. This value was multiplied by the air flow rate to get the total ventilation

Table 8: AHU parameters

Parameter	Abbreviation	Value
Minimum exhaust air temperature, °C	T_{exhaust}	-30
Extract air temperature, °C	T_{extract}	21.75
Ventilation air flow rate, l/s	q_{v}	4749
Supply air temperature, °C	T_{supply}	20.26
Heat recovery efficiency	η_{hx}	0.809

air volume supplied during the aggregation period. Consequently, although Equation 11 is formulated using ventilation heating capacity, its application with aggregated operation time and average outdoor temperature gives the corresponding heating energy use for the period.

The inputs for the analytical model were daily, weekly or monthly average outdoor temperatures, $T_{\text{out,real}}$ and $T_{\text{out,TRY}}$, calculated from hourly real and TRY climate data, respectively, for periods when the AHU fan speed, or operation rate, exceeded 54%; the aggregated AHU operation rate τ_i, derived from AHU electricity power $\Phi_{h,\text{el},i}$; and the period-integrated measured AHU heating capacity $\Phi_{h,\text{real}}$ for the corresponding aggregation period, hereafter interpreted as heating energy use for that period. In the aggregated calculation, τ_i represents the summed operation rate over the period and, when multiplied by the air flow rate, gives the total ventilation air volume used for calculating the heating energy correction.

3.2.2 Comparison of weather normalisation methods for post-retrofit baseline generation

Two approaches were applied to predict building energy use baselines at monthly resolution for the entire year. This thesis introduces one – a normalisation workflow that uses a fixed monthly degree-day (DD) method, an empirical engineering-based approach that utilises degree days to predict monthly energy use.

The inputs to the method include heating and cooling degree days, fixed base temperatures, the number of days in each month, and monthly metered or simulated energy use. For proper evaluation, the selected weather data span the years 2017–2021 with different weather conditions. The overall workflow of the method is illustrated in Figure 11 and can be summarised as follows: (1) Identification of the weather-dependent component of the energy use, (2) Normalisation of this component to base year weather conditions using a monthly weather normalisation coefficient (c_DD), to establish the baseline model, and (3) Utilisation of the weather normalisation in reverse to project the baseline and therefore predict energy use under the weather conditions of a specific year. This was used to compare the predictions with actual metered data.

The selected base temperatures - 10 °C for cooling (electricity energy use) and 15 °C for heating - were found to be most suitable for the generalisation.

Furthermore, threshold values were applied in the calculation of the normalisation coefficients, such that c_DD = 1 when CDDs < 60 and c_DD = 1 when HDDs < 50. The method identifies the weather-dependent component of energy use, normalises this component to base-year weather conditions using a monthly normalisation coefficient, and subsequently applies the normalisation in reverse to predict energy use under specific-year weather conditions.

In each case the degree-day method detected during the training period the weather dependent part of total heating energy use as 80–88%. The weather-dependent part from total electricity energy use is about 16-20% in the university facility (RB1) and 8–13% in the office building (RB2). The cooling demand data gathered from the building manager

revealed that the annual metered electricity for cooling in RB1 was marginal (1.1 kWh/m_2) in 2021. Therefore, it is uncertain whether the method detected the weather-dependent part incorrectly or whether some other use is dependent on weather, such as electricity for room lighting.

The machine learning method in Publication IV used a detailed weather dataset and was carried out in three phases: data pre-processing, clustering and scenario-specific regression modelling. The detailed description is in the Background.

The prediction methods were first validated in predefined conditions using data from simulation models and subsequently analysed with actual metered data from 2017 to 2022.

3.2.3 Application of weather normalisation methods

One practical outcome is that monthly AHU heating normalisation can be carried out with the HDD method if the base temperature and operation time are handled carefully. The analytical hourly model was slightly more accurate at daily and weekly normalisation, but it required AHU-specific parameters such as heat recovery efficiency and supply and extract air temperatures.

In the calculation of HDDs, the method used to determine the daily average outdoor temperature was also important: using only hours with fan speed above 54% resulted in a CV(RMSE) of 2.05%, compared with 3.95% when all 24 hours were included. This result shows that ventilation heating energy should not be normalised only against calendar weather conditions, but rather against the weather conditions during actual AHU operation.

Further analysis using the HDD method on metered AHU heating energy highlighted that normalisation is necessary for eliminating weather-related differences and for detecting changes in system operation or performance. In Figure 12, the annual AHU heating energy use was calculated for each month based on the previous 12 months of data. The figure shows that a change occurred from November 2021 onwards, requiring further investigation. Analysis of the BMS data revealed that the AHU airflow rate had been modified in November 2021.

In the study on baseline generation for post-retrofit savings assessment, monthly degree-day normalisation was compared with a machine learning method using hourly data. Validation with simulation data showed annual CV(RMSE) values of 1.4-10.4%, which satisfied the ASHRAE Guideline requirements for monthly baseline prediction. The machine learning models generally achieved higher accuracy than the degree-day method, particularly for heating energy prediction. The DD method that is based on degree-days and monthly energy use also showed sensitivity to weather differences between years, with prediction uncertainty in 2021 being 1-4.5% higher than in 2020. The model prediction percentage error was higher in summer months in 2021. The DD method showed high overestimation (about 2 times) in the office building (RB2) in June and July. Compared to the DD method, the machine learning method had minor percentage error only in June 2020 and July 2021. As in 2021 the cooling degree-days and direct solar radiation were higher, the high percentage error in the degree-day method could be caused by normalisation. The machine learning method is more accurate due to the use of independent variables such as hourly outdoor temperature and solar radiation.

When applied to metered data, the methods remained applicable but revealed the limitations of baseline prediction under changing building operating conditions. In the office building (RB2), the DD-model heating prediction achieved a CV(RMSE) of 19.3%, whereas the hourly machine learning models achieved CV(RMSE) values of 16.7-17.5%. For electricity prediction, the DD model achieved a CV(RMSE) of 6.91%, while the machine learning models achieved values of 6.11-6.18%. However, the measured energy use during

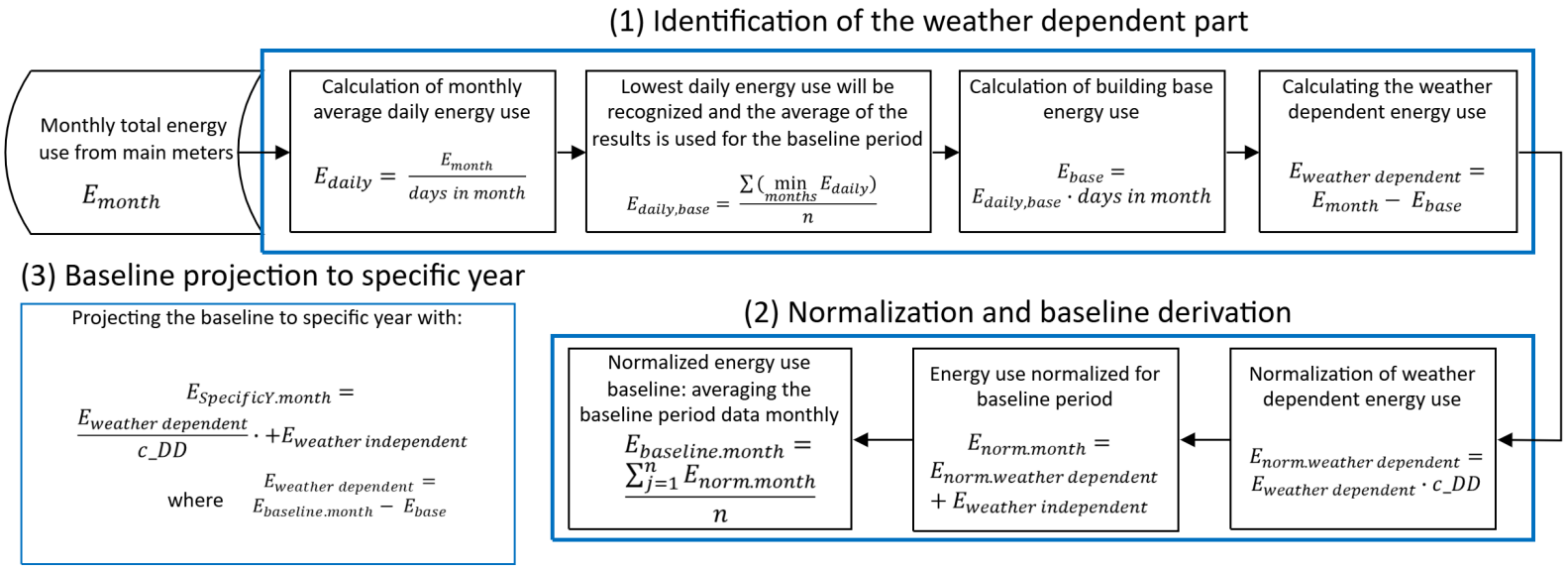


Figure 11: The flowchart of degree-day based method (n is the number of months used in the calculation phase).

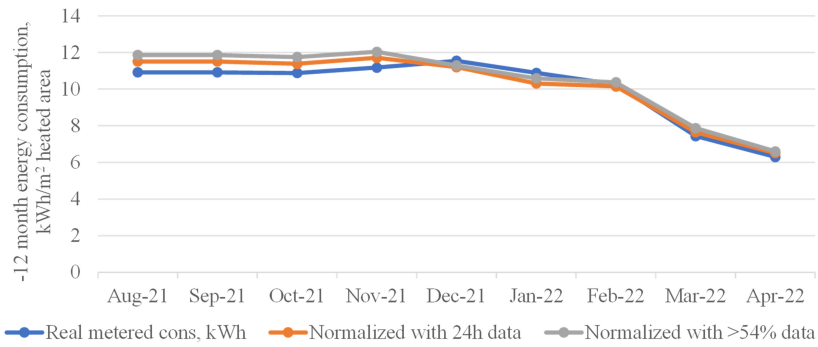


Figure 12: Annual AHU heating energy consumption calculated based on the previous 12 months of data

October–December 2019 was approximately 20% and 8% higher than predicted for heating and electricity, respectively (Figure 13).

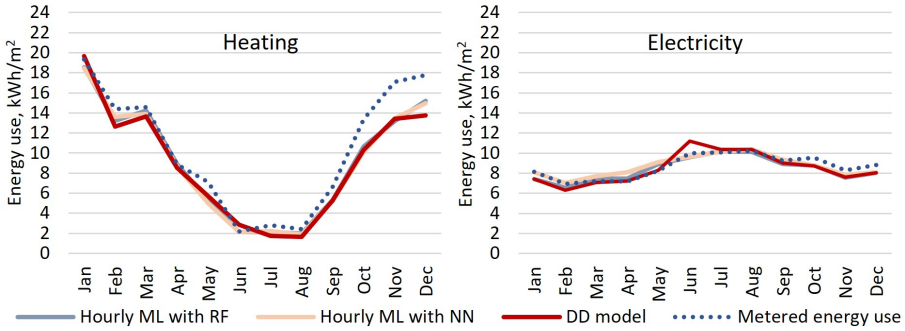
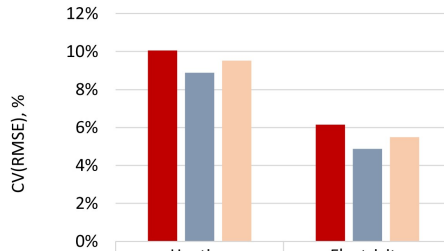


Figure 13: Metered heating and electricity energy use compared with three different model predictions in 2019 in RB2

Therefore, this period was assumed to include anomalies caused by external factors (for example, occupancy, system error or change in performance, etc.). When October–December were excluded from the CV(RMSE) calculation, the prediction uncertainty decreased considerably. Figure 14 shows that, in the pre-COVID office-building case, the heating prediction CV(RMSE) was 10.05% for the DD method and 8.88-9.52% for the machine learning methods. Electricity prediction was more accurate, with CV(RMSE) values of 6.15% for the DD method and 4.87-5.49% for the machine learning methods. In contrast to the validation phase using simulated heating energy data, the difference between DD and machine learning methods was relatively small when applied to metered data. Similarly, the uncertainty of electricity prediction did not differ substantially between the methods, although the machine learning models consistently achieved slightly higher accuracy.

During the COVID-period analysis, anomalous changes in building operation or use resulted in substantially higher heating prediction uncertainty in the university facility (RB1), with CV(RMSE) values of 30-40% as also shown in previous studies [64]. Excluding this anomalous heating case, the annual CV(RMSE) values generalised across both reference buildings were 11.5-19.3% for heating energy and 6.91-11.5% for electricity energy baseline prediction.



	Heating	Electricity
DD model	10.05%	6.15%
ML (Random Forest)	8.88%	4.87%
ML (Neural Network)	9.52%	5.49%

Figure 14: The uncertainty metric CV(RMSE) of prediction models in RB2 excluding the high energy use period (Oct–Dec 2019; i.e., calculation for 9 months).

3.2.4 Developed metered energy performance certificate normalisation workflow

The new application developed through Publications V– VI is a metered EPC normalisation workflow for non-residential buildings. The workflow begins with data pre-processing, after which non-EPB energy use is adjusted using either system-level or tenant-level normalisation methods. If hourly data are available and operation differs from the standard profile, operational-hours adjustment is applied. Heating energy is then weather normalised to the Estonian test reference year, typically with the HDD method. The adjusted and normalised energy use is converted to primary energy and compared with EPC class limits. This sequence enables metered-energy-based EPCs to be used for MEPS assessment while better reflecting the EPB scope and typical use.

3.2.4.1 Workflow for the separation of energy use outside the energy performance of buildings assessment boundary This thesis introduced the adjustment for non-EPB energy use as a normalisation method workflow that excludes energy uses not considered within the scope of the EPBD, using tenant meters. Non-EPB services were identified according to the regulatory framework.

In buildings where non-EPB services are measured through dedicated system-level sub-meters, their measured energy use can be subtracted from the total delivered energy before EPC calculation using Equation 15, where $E_{\text{adj,el}}$ represents energy use where non-EPB energy is excluded, E_{main} is the total energy use from the main meter and $E_{\text{non-EPB},i}$ is the measured system that belongs to non-EPB service. The unit for energy is kWh/a or kWh/m^{2}a heated floor area.

This approach is applicable only when non-EPB services are metered independently and interdependencies between systems, such as waste heat recovery for space heating, are properly accounted for.

$$E_{\text{adj,el}} = E_{\text{main}} - \sum_{i} E_{\text{non-EPB},i} \tag{15}$$

Where non-EPB services are embedded within tenant-level electricity measurements, a replacement-based normalisation procedure was applied using Equation 16, where $E_{\text{tenant,j}}$ is tenant electricity that includes non-EPB energy, metered with meter j, $E_{\text{tenant,STD},j}$ is the standard electricity use of tenant appliances and lighting for the relevant building type (Table 9). First, the measured tenant electricity was excluded from the main meter total.

Thereafter, standardised values for appliances and lighting, defined in the national EPC methodology, were reintroduced based on the tenant floor area. The example of non-EPB adjustment is shown also in Table 10.

$$E_{\text{adj,el}} = E_{\text{main}} - \sum_i E_{\text{non-EPB},i} - \sum_j E_{\text{tenant},j} + \sum_j E_{\text{tenant,STD},j} \tag{16}$$

This method is applicable when at least annual electricity use from both the main meter and the tenant meter associated with non-EPB uses is available.

For the tenant-level approach, it was assumed that all remaining energy, not attributable to non-EPB purposes, corresponded to appliances and lighting. Therefore, the tenant-level normalisation methodology is applicable only if there are no other technical systems intended to ensure indoor climate conditions (e.g., heat pumps or ventilation systems) connected behind the tenant's meter in addition to non-EPB energy, appliances, and lighting. Otherwise, the reduced energy use would no longer reflect the building's typical energy performance, as significant energy consumers would have been excluded.

Table 9: Standard annual energy use for appliances and lighting from the Estonian calculation methodology by building type

Building type	**Annual energy use, kWh/m^{2}a**
Office	31.5
Wholesale and retail trade service building	45.0
Educational building	15.4

Table 10: Example of non-EPB electricity adjustment using separately metered tenant energy use

Calculation step	**Specific annual electricity use, kWh/(m^{2}a)**	**Explanation**
Main electricity meter	245	Measured total electricity use from the main meter
Tenant electricity use: grocery store	-177	Excluded as metered tenant electricity use (including non-EPB energy use)
Remaining electricity use	68	Electricity use remaining after subtracting the metered tenant use
Standardised tenant electricity use, $E_{\text{tenant,STD},j}$	+45	Standardised appliance and lighting electricity use reintroduced according to tenant floor area
Adjusted electricity use, $E_{\text{adj,el}}$	113	Final electricity use after non-EPB adjustment

3.2.4.2 Workflow for operational-hours adjustment In this thesis, an operational-hours adjustment was introduced to account for differences between actual building operation and the standard-use assumptions defined in national regulations. Without operational-hours adjustment, buildings with extended operating schedules may appear less energy efficient than comparable buildings operating according to standard schedules, even when

the technical performance of the building is similar. After data pre-processing and non-EPB energy adjustment, the method consists of five steps: (i) identification of operational and non-operational hours; (ii) calculation of monthly average operational and non-operational loads; (iii) reconstruction of monthly energy use based on the identified schedules; (iv) validation of the reconstructed monthly energy use against measured monthly energy use using CV(RMSE) to assess the applicability of the method; (v) normalisation of energy use to the standard operational hours defined by regulation.

Actual operational hours were determined from occupancy-related access data provided by the facility manager and cross-checked using hourly electricity consumption profiles. In the multi-purpose university facility case study, separate annual schedules were established for weekdays, Saturdays and Sundays.

For each month, the average operational load, $P_{\mathrm{op},i}$, and non-operational load, $P_{\mathrm{non.op},i}$, were calculated from hourly data. Monthly energy use corresponding to standard operation was then determined according to Equation 17, where τ_{d} is the standard operational hours per day, τ_{w} is the standard operational days per week, and τ_{i} is the total number of hours in month i.

For mixed use, the monthly load was apportioned according to the floor area assigned to each functional use and normalised separately.

This approach requires hourly data for calculating monthly average power load and is therefore not applicable with only monthly or annual data. Furthermore, the user profile detection should be coordinated with information provided by the building owner or obtained during observation.

$$E_{\mathrm{adj}} = \sum_{i=1}^{12} \left(P_{\mathrm{op},i} \frac{\tau_d}{24} \frac{\tau_w}{7} \frac{t_i}{1000} \right) + \sum_{i=1}^{12} \left(P_{\mathrm{non.op},i} \left(1 - \frac{\tau_d}{24} \frac{\tau_w}{7} \right) \frac{t_i}{1000} \right) \tag{17}$$

The calculation example for the educational building case study is presented in Table 11 and in the following calculation for January:

$E_{\mathrm{adj}} = 8.83 \cdot \frac{11}{24} \cdot \frac{5}{7} \cdot \frac{744}{1000} + 4.57 \cdot \left(1 - \frac{11}{24} \cdot \frac{5}{7}\right) \cdot \frac{744}{1000} = 8.83 \cdot 0.327 \cdot 0.744 + 4.57 \cdot 0.673 \cdot 0.744 = 4.44\ \mathrm{kWh/m^2}$.

Table 11: Example of monthly electricity energy normalisation using operational-hours adjustment

Month	$P_{\mathrm{op},i}$, **W/m²**	$P_{\mathrm{non.op},i}$, **W/m²**	t_{i}, **h**	E_{adj}, **kWh/m²**
1	8.83	4.57	744	4.44
2	10.40	5.27	696	4.83
3	9.94	4.97	744	4.91
4	10.53	5.11	720	4.96
5	11.06	4.84	744	5.12
6	10.38	4.25	744	4.50
7	9.70	3.86	720	4.29
8	9.22	3.82	744	4.16
9	12.18	5.18	720	5.38
10	9.96	4.75	744	4.80
11	10.29	4.65	720	4.68
12	6.42	4.22	744	3.68
		Annual electricity energy use		**55.8**

3.2.5 Application of the metered energy performance certificate normalisation workflow

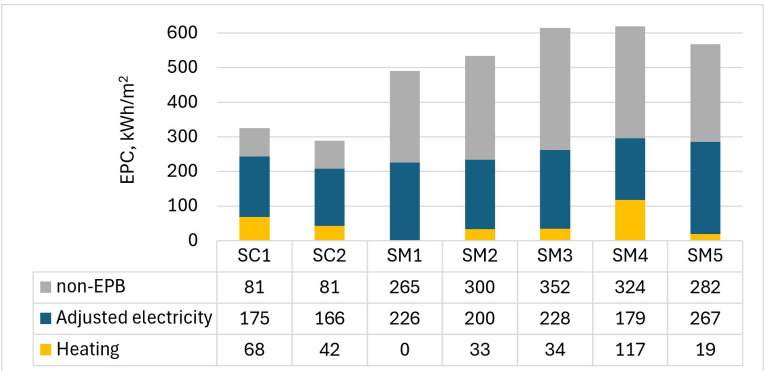
3.2.5.1 Separation of energy use outside the energy performance of buildings assessment boundary

The effect of non-EPB adjustment was approximately 50%. In Supermarket 1 (SM1), the EPC based on main meters was 490 kWh/m^{2}a, corresponding to class G. After system-level adjustment, electricity energy use was reduced by 55% and the corrected EPC was 221 kWh/m^{2}a, corresponding to class D. The tenant-based approach was tested using two values: (i) total metered energy use, and (ii) the grocery store's energy use (including refrigeration, appliances, and lighting). That gave a similar result, 226 kWh/m^{2}a, representing a 54% reduction.

In Supermarket 2 (SM2), system-level non-EPB energy meters were available. The non-EPB adjustment reduced primary electricity energy use by 56% and changed the EPC from 533 kWh/m^{2}a, corresponding to class G, to 233 kWh/m^{2}a, corresponding to class E. The shares of non-EPB services and appliances in the EPC were 43% and 7.2%, respectively. The calculated EPC was 149 kWh/m^{2}a, corresponding to class A, which made the performance gap visible. The 36% difference may reflect operational inefficiencies or limitations of the assessment methodology, warranting further investigation into the causes of the performance gap.

The calculated EPC in supermarket 3 was 205 kWh/m^2, corresponding to class C. In this building, non-EPB energy was not metered separately; however, the tenants' electricity energy use, which includes non-EPB energy, was measured (here as Grocery store). Applying a tenant-level methodology improved the EPC from class G to class B (148 kWh/m^2), representing a 76% reduction in primary energy use. However, Grocery store includes other end-uses that do not fall under appliances and lighting but still are considered as typical use (e.g., ventilation, cooling, water heater). In such cases, it is essential that the EPC assessor identifies which loads fall under subtractable non-EPB energy and ensures they are properly accounted for in the EPC calculation. This can be achieved, for example, by measuring average power with a clamp meter and incorporating the operating time of the technical system in the calculation. In this study, such measurements were not conducted. However, to give an example, proportions for HVAC (14%) and Property (8%) were taken from previous case studies to estimate their share of energy use within the "Grocery store" category. The corrected EPC was 262 kWh/m^2, representing a 57% reduction. This result is similar to findings from previous case studies, and more realistic compared to the calculated EPC.

The summary of the non-EPB separation cases in Figure 15 shows that non-EPB adjustment can reduce PE by more than half in retail buildings and can change EPC results by one or two classes.



	SC1	SC2	SM1	SM2	SM3	SM4	SM5
non-EPB	81	81	265	300	352	324	282
Adjusted electricity	175	166	226	200	228	179	267
Heating	68	42	0	33	34	117	19

Figure 15: Shopping centers (SC) and retail buildings (SM) EPB and non-EPB primary energy use

The method was validated against a detailed supermarket simulation model representing standard EPB energy use. For Supermarket 1, the standard simulation EPC was 182 kWh/m^{2}a, while the corrected metered EPC remained 44 kWh/m^{2}a, or 19%, higher. This was interpreted as a conservative result because the metered value still included effects such as refrigeration heat losses, dehumidification and auxiliary systems not fully represented in the standard model. The normalisation therefore separated non-EPB energy while preserving a more realistic indication of the remaining EPB.

3.2.5.2 Application of the operational-hours adjustment Results showed that operational hours can significantly distort metered EPC values in non-residential buildings. First, a calibrated simulation model of a university facility with office-like extended use was used to test a simplified operational-hours adjustment. Before normalisation, the REAL model differed from the standard model by 16-25% in electricity energy use. Heating energy differences were smaller, 8-10%, but monthly heating percentage errors varied between 4% and 15%. After applying the adjustment, using the total hours when the building was occupied gave the most accurate result. For electricity, CV(RMSE) was approximately 1.3-1.5% in the best cases. For heating, using all operational hours gave CV(RMSE) of approximately 1-2.5%, with monthly errors of 0.3-7.4%.

The impact on primary energy was also clear. Figure 16 shows that the simulated PE use of the extended-hours building was 221 kWh/m^{2}a, or 237 kWh/m^{2}a when base load was included, corresponding to class E. After operational-hours normalisation and weather correction, the values were reduced to 189 and 210 kWh/m^{2}a, respectively. These results were close to the standard-profile model values of 187 and 208 kWh/m^{2}a, and the EPC class moved from E to D. The result demonstrates that extended use can make a building appear worse than it would under standard conditions, and that a simple hourly-load method can correct most of this effect.

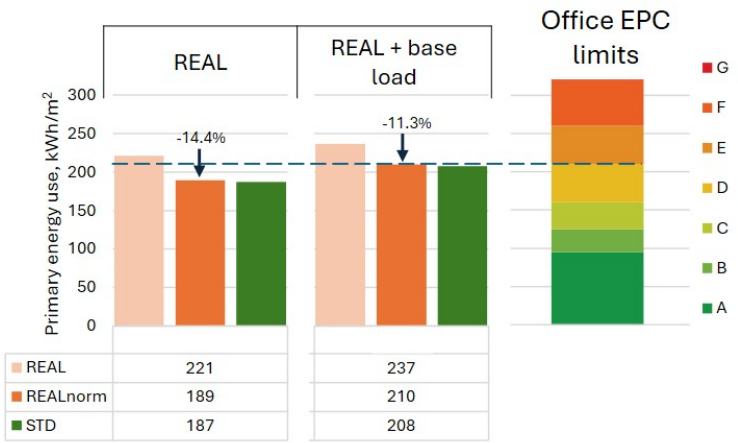


Figure 16: The primary energy use of the normalisation versions for two models

Later, the operational-hours adjustment method was applied to metered data from the multi-purpose university facility. First, non-EPB energy was subtracted from the hourly data, reducing the EPC from 275 kWh/m^{2}a, class F, to 196 kWh/m^{2}a, class D. Then operational-hours normalisation reduced electricity PE by 17.3 kWh/m^{2}a (14.0%) and heating PE by 6.4 kWh/m^{2}a (10.1%) (Figure 17). After weather normalisation, the EPC decreased by about 12.8%, from 196 to 171 kWh/m^{2}a. The class remained D, but the value became more comparable with buildings operating under standard schedules.

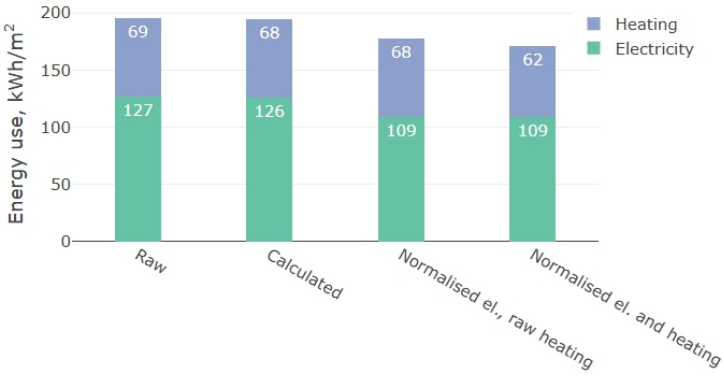


Figure 17: The weather normalised primary energy use comparison between different calculations

Validation against the standard simulation model confirmed that the operational-hours adjustment was conservative. Figure 18 shows that the calibrated model had a PE use of 190 kWh/m^{2}a, whereas the standard model had 162 kWh/m^{2}a. The operational-hours-normalised metered result was approximately 2.4% higher than the standard model result. This difference was mainly attributable to the non-EPB base load. The result supports the use of the operational-hours adjustment method for metered EPC assessment, but also demonstrates that non-EPB base loads have a significant impact on the adjustment and should therefore be carefully addressed before applying the method.

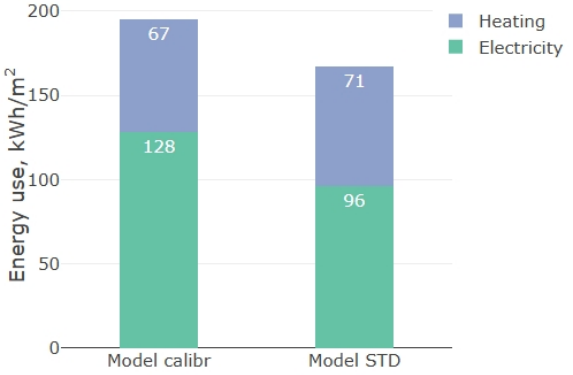


Figure 18: The weather normalised primary energy use comparison between calibrated and standard (STD) simulation models

Table 12: Summary of normalisation method results.

Normalisation problem	Main result	Suggested method
AHU heating weather normalisation	Analytical model was slightly more accurate daily and weekly; monthly HDD normalisation performed similarly when specific base temperature and AHU operation were considered.	Use HDD for monthly AHU heat-coil normalisation with AHU-specific base temperature and operation-time filtering. Use the analytical model, if daily or weekly accuracy is needed and hourly metered data are available.
Whole-building baseline generation (weather normalisation)	Simulation validation CV(RMSE) was 1.4-10.4%; machine learning improved monthly heating prediction, while DD remained acceptable for annual/monthly savings if uncertainty is reported.	Use machine learning when hourly data and weather variables are available; use DD for simpler monthly baseline assessment with sensitivity reporting.
Non-EPB energy separation	Retail case studies showed at least about 50% PE reduction after excluding or replacing non-EPB loads; EPC classes changed by one or two classes.	Use system sub-meters where available; otherwise use tenant-meter subtraction with standard appliance and lighting replacement (Equation 18). The tenant-level normalisation methodology is applicable when no technical systems related to indoor climate control (e.g., heat pumps or ventilation systems) are connected behind the tenant meter. $$E_{\text{adj,el}} = E_{\text{main}} - \sum_i E_{\text{non-EPB},i} - \sum_j E_{\text{tenant},j} + \sum_j E_{\text{tenant,STD},j} \quad (18)$$
Operational-hours adjustment	Extended operation changed EPC values by about 11-25%; adjustment reduced PE by 14.0% for electricity and 10.1% for heating in the metered case.	If the operational hours differ from typical use, apply the operational-hours adjustment using hourly average monthly loads during operational and non-operational periods multiplied by standard hours (Equation 19). $$E_{\text{adj}} = \sum_{i=1}^{12} \left(P_{\text{op},i} \frac{\tau_d}{24} \frac{\tau_w}{7} \frac{t_i}{1000} \right) + \sum_{i=1}^{12} \left(P_{\text{non.op},i} \left(1 - \frac{\tau_d}{24} \frac{\tau_w}{7} \right) \frac{t_i}{1000} \right) \quad (19)$$

4 Discussion

The motivation of this thesis arises from climate-neutrality goals and policy instruments such as MEPS and credible EPCs. The six publications form a logical progression from the identification of the performance gap and renovation barriers to methodological development and policy interpretation. Publication I showed that current commercial renovation practice leaves a 40-50% renovation gap and that commercial building energy use includes substantial non-EPB loads. This highlighted the need for both policy improvement and more accurate EPC assessment methods based on metered energy data. Publication II then showed that reaching the NZEB level in an office building is technically possible, but economically difficult due to a long payback time. Publications III– IV contributed to the assessment of system performance and operational energy savings using weather normalisation and baseline prediction methods. Publications V– VI addressed the methodological need for better EPB assessment methods by developing methods for converting measured energy use into a comparable operational EPC value through non-EPB adjustment and operational-hours correction.

The market-based renovation analysis conducted in 2020 showed that achieving credible EPCs and NZEB-level renovation in non-residential buildings requires both reliable energy performance assessment methods and policy measures that address the investment logic of commercial real estate. Since then, the political, economic and energy policy context has changed considerably, driven by the energy crisis, inflation, revised EPBD requirements and the introduction of MEPS. Despite these changes, the fundamental barriers identified in this thesis remain largely unchanged. A market analysis published in 2023 [17] outlined continued low interest in energy-efficiency investments, a preference for projects with short payback time, and uncertainty caused by the variable quality of energy audits and renovation proposals. These findings indicate that the challenges identified in this thesis remain relevant and highlight the continuing need for robust assessment methods and practical renovation solutions for non-residential buildings.

4.1 Performance gap and market-based renovation

In this thesis, the performance gap is defined as the difference between calculated or predicted energy performance and measured energy use, expressed where applicable through the calculated and operational EPC. A meaningful comparison requires consistent EPB boundaries and normalisation to comparable weather and use conditions. However, Publication I showed that non-EPB electricity can account for a substantial share of energy use in commercial buildings, potentially distorting the assessment of the performance gap unless excluded. Previous studies have indicated that non-EPB electricity uses may account for about 20% of electricity use in hardware stores, up to 80% in grocery stores and 50-70% in office buildings [14, 37]. Publication VI further clarified this issue by showing that a large share of measured energy use in commercial buildings is not regulated EPB energy. In grocery stores, this includes refrigeration, kitchens and other process loads, while in office buildings it includes server rooms, elevators and outdoor lighting. If these loads are included in the main meter and directly converted into an EPC value, the resulting assessment may classify a building as inefficient even when part of the measured energy use is outside the EPB assessment boundary. This was demonstrated in Publication VI, where the non-EPB adjustment reduced primary energy use by at least about 50% in several retail cases and changed the EPC class by one or two classes.

Differences in user behaviour and operational hours from standard assumptions can also affect the comparisons between calculated and measured energy performance or

between buildings. Publication VI showed that adjusting for extended operating hours in a university facility building reduced energy use by approximately 12%. Publication V used a simulation model to validate the method and reported reductions of 11%-14.4% after operational-hours adjustment. Furthermore, Publication VI indicated that outside operational hours in the university facility, the electrical power load was around 4-5 W/m^2. However, in standard calculations, the non-residential building base load is near zero as the appliances and lighting do not work outside operational hours. These two aspects will influence substantially the performance gap between metered energy use and the EPB assessment boundary. By aligning energy data with standardised operational hours, this adjustment framework enables fairer comparisons across buildings with different usage patterns, including those with extended or reduced operating hours.

To enable a consistent assessment of the performance gap, energy performance assessments of existing buildings should be made more comparable to design phase calculations. However, this is only a partial solution. As Menezes et al. highlighted, design-phase energy performance assessment also needs to be more realistic considering post-occupancy evaluation. Their study showed a great reduction of the performance gap, reaching a gap to only 3% instead of the two-thirds difference between the simulation model and metered energy use. [32] Regarding after-hours work, NABERS provides guidance for offices [65], suggesting that its influence should be adjusted in asset ratings because modern office buildings typically maintain persistent equipment and lighting loads outside standard operating hours. Together, more realistic standard-use assumptions, exclusion of non-EPB energy use and operational-hours adjustment can improve comparability, allowing the remaining performance gap to better reflect differences within the EPB assessment boundary. However, caution is required to avoid excessive normalisation.

The normalisation results based on metered energy demonstrate that separating non-EPB energy and applying operational-hours adjustment remain conservative measures and do not remove the performance gap. In the supermarket validation case in Publication VI, the corrected metered EPC remained 44 kWh/m^{2}a, or 19%, higher than the standard simulation result. When the operational-hours adjustment was applied to metered data, the difference compared with the typical-use simulation model was 2.4%. These conservative results reduce the risk of understating energy use under standard conditions and the associated performance gap. Otherwise, the building energy performance could be overestimated, and the need for renovation or compliance with future MEPS could be assessed incorrectly. Nevertheless, normalisation based on measured energy use remains preferable because simplifications are inevitably introduced both in the input assumptions and in the simulation calculations.

Publication I showed that market-based renovation in Estonian commercial buildings does not usually reach the class C level required for NZEB major renovation. Office-building renovations improved energy performance only marginally, and a gap of about 40% remained after market-based renovation. In trade buildings, about one third of the buildings reached the NZEB level, whereas the remaining buildings had a gap of about 50%.

The main barriers to renovating to the NZEB level were found to be the long payback times of renovations, a lack of motivation among tenants to share the investment cost due to the small share of the energy cost, and a high investment risk for building owners driven by uncertainties regarding both renovation measures and future EPC assessment methods. Furthermore, the investment logic of landlords often limits renovation activity. In short-term investment cases (3-10 years), landlords are generally not interested in deep renovation because properties are expected to be sold before major technical upgrades become necessary. Long-term investors (20-30 years) are more interested in renovation

because technical systems typically require upgrading within this period. However, the situation may change as energy performance becomes important in property valuation, investment decisions and financing. Financial institutions and investors are expected to place greater emphasis on energy efficiency, making energy-efficient buildings more attractive investment assets. Furthermore, green policies and certification schemes such as LEED and BREEAM may increase the willingness of landlords to invest in energy renovation. However, broader implementation of deep renovation would likely require both higher energy or carbon costs and financial incentives that reduce renovation payback times.

One aspect identified both in the interviews reported in Publication I and in the literature review was that there is insufficient knowledge about actual building energy performance and uncertainty regarding the return on investment from renovations. Publication II showed that the NZEB major renovation target can be reached technically, but not under typical market-based investment conditions. In the office-building case study, reaching the NZEB level required a wider package of measures, including lighting replacement, improved AHU performance, better automation and ventilation control, night setback of indoor temperature, window replacement and a 69 kW photovoltaic system. With these measures, the primary energy use was reduced close to the NZEB major renovation level, but the package payback time remained around 30 years. However, Publication I showed that for market-based renovations landlords normally preferred payback times below 10 years, and in the case of government grants, they would probably accept longer payback periods of 12–15 years.

4.2 Role of user behaviour

User behaviour plays a substantial role in the energy performance assessment of non-residential buildings. Publication IV showed that baseline prediction reliability depends on whether the training period represents normal building operation. Validation with simulated data showed low uncertainty on a monthly scale. However, when the baseline prediction was applied to metered data, the comparison between the COVID and post-COVID periods revealed a strong influence of user behaviour and building utilisation. In the university facility case (RB1), the annual heating energy prediction uncertainty increased to 30-40%. This was primarily caused by the training dataset representing the main COVID period (July 2020-July 2021), during which building occupancy decreased, while AHU operating hours increased, resulting in substantially higher heating energy use than in the following year. Caution is required because non-residential buildings may exhibit greater variability than residential buildings during abnormal events such as the COVID-19 pandemic. Therefore, methods for detecting unusual changes in energy use, including dynamic normalisation and anomaly-detection approaches, are needed together with the baseline prediction methods.

Another important aspect concerns the definition and detection of operational hours in non-residential buildings. Actual building operation may be described using several indicators, such as opening hours, occupant presence, access logs or AHU operating schedules. Publication V therefore analysed different approaches for detecting operational hours and showed that occupancy-based schedules provided the most suitable unified method for both electricity and heating energy normalisation. At the same time, buildings differ considerably in their use patterns, and therefore the final decision should remain with the EPC assessor, who should select the method that best represents the operation of the assessed building.

Another issue relates to the definition of standard-use hours in mixed-use buildings. Estonian national energy-efficiency regulations define fixed operational hours for 12 building

categories according to the European Standard EN 16798-1 [63]. However, many non-residential buildings contain multiple functions with different occupancy profiles. In Publication VI, the analysed educational building consisted approximately equally of office spaces and auditoriums. The main calculations therefore used mixed occupancy schedules. When the assessment was conducted using only educational-building schedules, the primary energy use was 4 kWh/m^2 lower, whereas office-only schedules resulted in 8 kWh/m^2 higher values compared with the mixed-use case. This difference corresponded to an approximately 7% variation in the normalised result, demonstrating that the selection of standard operational hours has a substantial effect on EPC assessment. One practical approach is to classify buildings according to their dominant floor-area use, although this may not always represent actual building operation. Therefore, the impact of occupancy-profile selection should be investigated further in future studies.

4.3 Reliability of energy performance of buildings assessment

Operational EPC assessment is preferable because it is based on metered data and provides feedback on actual building performance. However, the metered data also include energy uses not related to EPB and usually reflect real weather. The analyses in Publications IV–VI showed that these effects can be corrected only if the metering structure, operational schedules and weather dependence of energy use are sufficiently known.

Reliability of non-EPB separation and operational-hours adjustment. Depending on tenant activities, electricity use may contain both EPB-related standard uses and non-EPB process loads. If the whole tenant meter is subtracted from the main meter, EPB-related lighting and appliance energy may be removed as well, leading to underestimation. Publication VI addressed this by excluding measured tenant electricity and then reintroducing standard appliance and lighting energy according to the national EPC methodology. However, the tenant-level normalisation methodology is applicable when no technical systems related to indoor climate control (e.g., heat pumps or ventilation systems) are connected behind the tenant meter. Otherwise, the reduced energy use would no longer reflect the building's typical energy performance, as significant energy consumers would have been excluded.

Publications V and VI analysed the operational-hours adjustment method and showed that the deviations from standard operational hours can influence the metered energy use by 11-14%. However, several limitations and practical considerations should be noted.

First, if a building includes non-EPB energy uses and operational-hours adjustment is applied without prior separation of these uses, the resulting EPC will also reflect non-EPB energy uses. In Publication VI the initial EPC calculated from metered energy use was 275 kWh/m^2, which belonged to class F. However, in addition to EPB uses, the building also included non-EPB energy uses such as servers, associated cooling systems, and outdoor lighting. Therefore, before operational-hours adjustment, the adjustment for non-EPB energy use was performed on an hourly basis resulting in an EPC of 196 kWh/m^2, and the class was D. This hourly subtraction requires careful treatment of missing data. In this study, 74% of hourly values were missing in December and over 40% in January, June, July and November. However, for electricity use, validation CV(RMSE) was 4.8% when all months were included and 5.1% when only months with less than 25% missing data were retained - the uncertainty increased by 0.4%. The corresponding EPC reductions after operational-hours normalisation were 12.8% and 11.2%, respectively.

Secondly, caution is required when adjusting heating energy use to standard operational hours. In Publication VI, the air-handling unit accounted for 50% of heating energy use, resulting in substantially higher heating demand during operational hours than during

non-operational hours. Comparison with the standard-use simulation model showed higher heating energy use in the standard-use case due to dynamic effects, which were not captured by the normalisation procedure. Therefore, the operational-hours adjustment for heating energy use should be further refined, as simplified normalisation does not fully capture the dynamic thermal behaviour of buildings.

The purpose of these adjustments is to improve comparability while retaining differences attributable to building and technical system performance. In the tenant-meter approach, indoor climate control systems remain within the assessment boundary, while measured tenant lighting and appliance energy is replaced with standard-use values. The operational-hours adjustment retains measured average loads during operational and non-operational periods but adjusts their duration to standard schedules.

Reliability of weather normalisation. Publication III showed that in the analysis and normalisation of AHU heat coil energy use, the operating time of the AHU fans should be considered when calculating HDDs as it affects the accuracy of base temperature determination. Furthermore, weather normalisation is essential for removing weather-related variation and for detecting changes in system performance or operation as presented with annual AHU heating energy use that was calculated for each month based on the previous 12 months of data. Publication IV continued with total heating related weather normalisation. In both renovation projects and the application of minimum energy performance standards, it is important to be able to verify achieved energy savings. Therefore, it is necessary to establish an accurate energy use baseline to assess the changes in energy use resulting from building renovation. Publication IV analysed two weather normalisation methods and showed that machine learning methods achieved lower uncertainty than the degree-day method, but require more data and effort. The degree-day method provided a practical and sufficiently accurate solution when only monthly data were available. However, it is recommended that monthly percentage errors or annual mean absolute percentage error (MAPE) are reported alongside the energy savings assessment to provide transparency regarding the uncertainty of the results.

Reliability of data. The aim of this thesis was to develop methods that are as simple as possible and require a minimum number of input parameters from building energy meters and stakeholders. The rationale for this is the current low quality of available data. From an Estonian perspective, only a limited number of buildings are equipped with sub-metering that records hourly data, and in many cases even the main meters are not measured on an hourly basis. Older buildings often lack smart meters altogether, with energy use typically obtained from monthly readings. Furthermore, the operational-hours adjustment study highlighted the need for further investigation into missing hourly records, methods for treating these data gaps and their effects on normalisation accuracy. However, the revised EPBD (2024) introduces requirements for building automation and control systems in non-residential buildings [22]. In general, newer buildings are equipped with more advanced metering systems, and data quality is improving. The operational-hours adjustment method relies on hourly energy use data, and future studies should focus on data-driven and AI-based methods for energy performance assessment, which are already appearing.

4.4 Simulation-based methodology workflow for energy performance of buildings assessment

In this thesis, energy simulation played a substantial role in method validation in Publications II and IV– VI and the methods were thereafter tested on metered energy use.

Figure 19 summarises the simulation-based workflow used to support this interpreta-

tion. The workflow starts from the real building, where measured heating and electricity data, metering structure, technical documentation and information on building operation are collected. These data are then used for compiling the simulation model. Simulations were conducted using actual weather data or the test reference year (TRY). The simulation results are then compared with metered energy use. If the uncertainty is acceptable according to the selected calibration criterion, for example CV(RMSE) below 15%, the model can be used for further assessment. If the uncertainty exceeds the criterion, the model should be revised when the deviation affects the analysis, or used with caution when the deviation is not relevant to the specific assessment purpose. If the uncertainty substantially exceeds the selected calibration criterion, the simulation model should be revised and adjusted according to the observed building operation, after which the calibration process should be repeated.

The workflow applied in Publications IV– VI can therefore be interpreted as a stepwise method for simulation-based methodology using building technical and metered data. Publication IV used calibrated simulation models to compare degree-day and machine learning baseline prediction methods and to quantify their uncertainty. Publication V validated the operational-hours adjustment method using simulation, showing how deviations from standard operating hours affect heating and electricity use. Publication VI then integrated operational-hours and non-EPB normalisation into metered EPC assessment and used detailed dynamic simulation to validate the corrected metered results. In Publication II the measured energy consumption, the calibration method of energy simulation, and identification of energy renovation measures were the tools to discover the improvement of the energy performance to NZEB-level of major renovation.

The reliability of the simulation-based methodology depends strongly on the quality of the input assumptions related to occupancy, operational schedules, internal gains and electricity use and how accurately they reflect actual building operation. However, the results from Publications II and IV– VI indicate that calibrated simulation models remain a useful tool for reliable EPB assessment.

4.5 Implications for energy performance of buildings policy

Recent EU regulations direct towards more accurate and comparable energy performance assessment methods within EU Member States. However, it has been realised that EPC ratings are not yet well comparable between Member States. One reason is the variation in national calculation methodologies, while another is the ability to detect the occupancy and climate variations while assessing the energy performance of buildings. Quantifying and making the energy performance gap visible is essential for better understanding the current state of the building stock. Moreover, actual performance should be assessed using metered energy use to reflect the real performance, thereby improving the asset rating methodologies as well as building energy performance benchmarks and thresholds.

This thesis addressed key methodological challenges related to metered EPB assessment and developed approaches for normalising measured energy use in non-residential buildings. Incorporation of the developed procedures into the Estonian assessment methodology represents a practical contribution of this research. Separating non-EPB energy use using tenant-level metering and adjusting metered energy use for variations in operational hours can improve the credibility of EPCs in Estonia by enabling fairer comparisons between buildings. The developed methods could also be adapted for use in other Member States, both for calculating EPCs from metered energy use and for routine EPB assessment and monitoring, by applying national standard values for appliance and lighting energy use and operational hours. However, inclusion in the national methodology does not guarantee that

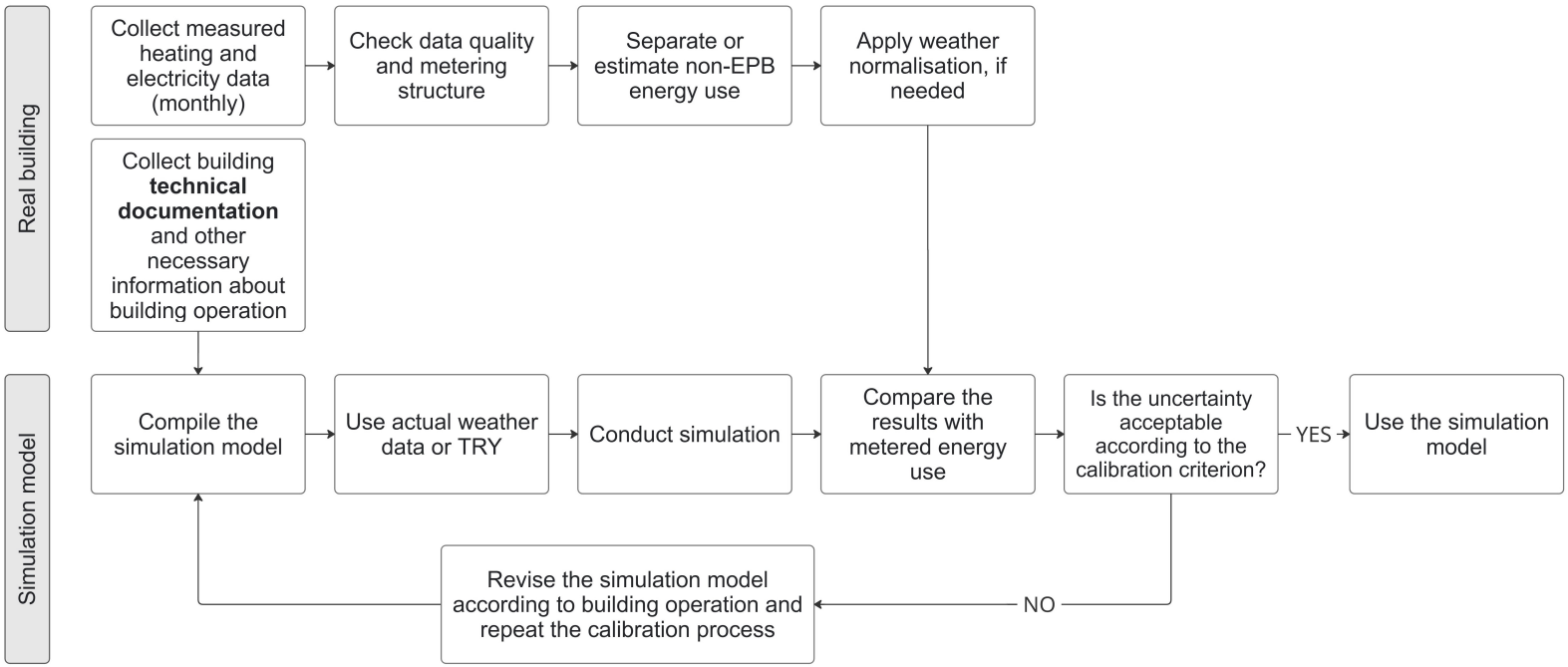


Figure 19: Simulation-based methodology workflow

the methods can be widely applied in practice. The methods showed robust performance in the analysed case studies and have potential applicability across different building types, provided that suitable measurement infrastructure and assessor competence are in place. Tenant-level metering is not available in all non-residential buildings in Estonia, which limits the applicability of the non-EPB separation method. Similarly, the operational-hours adjustment requires hourly energy data, data pre-processing and additional assessment time.

The results indicate that further development of EPC methodologies is still needed. In particular, current standard-use assumptions may not adequately reflect modern office buildings, which often maintain persistent loads outside standard operating hours. Furthermore, the impact of occupancy-profile selection on operational EPCs should be investigated further, especially in mixed-use buildings. As buildings become increasingly digitalised and equipped with advanced metering systems, future research should focus on data-driven assessment methods, automated normalisation procedures, and improved building data management to support reliable operational EPC and MEPS implementation.

5 Conclusions

Current climate-neutrality goals and policy instruments such as MEPS and EPC increase the need for credible EPB assessment methods within the European Union. This thesis aimed to research current energy use and renovation practices of commercial buildings in Estonia and develop approaches for EPB assessment to improve the comparability of EPCs.

5.1 Commercial building renovation practice and performance gap

Following market-based renovations, primary energy use exceeded the NZEB threshold by 50% in over 65% of retail buildings, and by 40% in all office buildings. In addition, a substantial part of the measured energy use was outside the EPBD scope, i.e., representing unregulated uses not considered in the EPC calculation.

The selection of market-based renovation measures was found to be strongly correlated with the payback time. The most used measure in trade buildings was the modernisation of building automation and in office buildings, the demand-controlled ventilation or ventilation automation renovation. The preferred payback time was below 10 years. However, the NZEB major renovation case study showed a 30-year payback time including a wider package of measures, including lighting replacement, improved AHU performance, better automation and ventilation control, night setback of indoor temperature, window replacement and a 69 kW photovoltaic system.

The convenient renovation cost to real estate companies in Estonia was only about 10 €/m^2 and the internal rate of return (IRR) of the measure package was around 20%. This is far from the investment of the renovation package to the NZEB level of about 130-150 €/m^2 and the IRR below 10%. Thus, the main barrier to NZEB-level renovation was economic feasibility: the investment was considerably higher, while the expected return was lower and the payback time longer than what real estate companies typically considered acceptable.

To overcome the renovation barrier, interviewees recommended preparing new energy or carbon taxes together with incentives for energy efficient renovations. Knowledge development about cost-optimal measures was seen also as important to control the risks of renovating to the NZEB-level. Furthermore, real estate companies prefer to know about the change of regulations in advance for a longer period and more stable boundaries to estimate the risk of investment.

Energy renovation measures and savings to improve the energy performance to the NZEB level were identified in a large (16 990 m^2 heated area) office building. For that purpose, energy use was measured, a simulation model was developed and calibrated, and feasible and more comprehensive energy improvements and costs were analysed. Improvements to lighting, AHU, heating, the installation of a 69 kW PV system, and window replacement were needed to achieve the NZEB major renovation with a primary energy use of 163 kWh/m^2. However, some of the applied measures had long payback times of 40-70 years and are not realistic to be implemented without renovation incentives.

In parallel with improving commercial buildings' energy efficiency, reliable quantification of the performance gap is essential for understanding the actual state of the building stock. Results showed that a substantial share of energy use in commercial buildings may consist of non-EPB electricity. In several retail buildings, non-EPB energy accounted for approximately 50% of total electricity use. If these energy uses are not separated, the resulting EPC no longer represents EPB energy use and is not comparable with EPC benchmarks, NZEB targets, or future MEPS requirements.

5.2 Development of energy performance of buildings assessment methods

The EPB assessment methods needed for both energy saving and credible EPC calculation are analysed and validated. The result is a sequence of EPB assessment methods from separation of non-EPB energy uses, followed by operational-hours adjustment and weather normalisation. This thesis developed and validated a methodology for separating EPB and non-EPB energy use by combining main-meter data with tenant electricity-meter information. The results showed that non-EPB adjustment can reduce primary energy use by more than half in retail buildings and can change EPC results by one or two classes. The proposed method enabled the separation of regulated building energy use from tenant-related loads and improved the comparability of measured energy performance between buildings. Validation with simulation models showed that the method remained slightly conservative while making the performance gap visible when compared with calculated EPC values. The results demonstrate that energy used to condition the indoor environment can be separated from metered energy data by combining main-meter measurements with tenant electricity-meter information and allocating tenant-related electricity uses outside the EPB boundary. Tenant electricity meters provide a practical data source for identifying and quantifying non-EPB energy uses, enabling the calculation of operational EPCs that are comparable with calculated EPCs, EPC benchmarks and future MEPS requirements.

Actual operational hours in non-residential buildings may differ substantially from the standard operating schedules assumed in EPC calculations and can therefore influence measured energy use considerably. This thesis developed and validated an operational-hours adjustment methodology to normalise measured energy use to standard use conditions. The results showed that buildings with extended operation may consume significantly more energy than assumed in standard occupancy schedules and that this effect can influence the operational EPC assessment. Application of the method reduced primary energy use by approximately 12% in a building operating longer than standard assumptions.

The methodology reconstructed monthly energy use from operational schedules and power-load profiles and demonstrated good agreement with measured energy use. Validation with dynamic simulation models showed that the method remained slightly conservative while improving comparability with standard-use conditions. The results demonstrate that operational-hours adjustment enables measured energy use to be converted to typical occupancy conditions and therefore improves comparability between buildings with different operational schedules.

Weather conditions have a significant impact on measured energy use and therefore must be normalised before metered energy data can be used for EPB assessment. This thesis developed and validated weather normalisation methods for ventilation heating energy use and post-retrofit baseline generation. The analytical ventilation heating normalisation method provided more accurate results than the traditional heating degree-day approach because it explicitly accounted for heat recovery efficiency, supply air temperature and operational schedules. However, the analytical model requires more detailed input data. Therefore, in some cases the HDD method may be a more practical solution, provided that an appropriate base temperature is used and operational hours are taken into account, as both significantly influence the results.

For post-retrofit energy baseline generation, both degree-day and machine learning methods achieved acceptable accuracy, but machine learning models showed lower uncertainty and better monthly prediction performance. When applied to metered data, the methods remained applicable, but also revealed the limitations of baseline prediction under changing building operating conditions. During the COVID-19 period, anomalous

changes in building operation and occupancy resulted in substantially higher heating-energy prediction uncertainty in the University Facility, with CV(RMSE) values of 30-40%.

This thesis demonstrates the significant impact of non-EPB energy use, extended operational hours, and weather conditions on the energy performance of non-residential buildings and on the resulting assessment outcomes. The results show that the proposed normalisation methods can be applied with sufficient accuracy for operational energy performance assessment. However, the availability and quality of data remain important limitations. Anomalies caused by external factors, such as changes in occupancy, system operation, faults, data gaps, or building performance, should be carefully identified and justified before the normalised results are used for energy performance assessment.

5.3 Practical outcomes

Contribution to knowledge

This thesis provided a systematic assessment of the gap between market-based renovation practice and major NZEB-level renovation in Estonia. The results showed that current commercial building renovation practice improves energy performance only marginally, leaving a gap of approximately 40-50% compared with NZEB renovation targets. The analysis identified the main barriers to deep renovation as the long 20-30 year payback time, low internal rate of return, uncertainty associated with major renovation measures, and the limited financial motivation of tenants due to the relatively small share of energy costs in total occupancy costs. Furthermore, the work demonstrated that reliable EPC assessment methods are essential for quantifying and making the performance gap visible, as a substantial share of measured energy use in commercial buildings may consist of non-EPB energy use.

This thesis provides new knowledge for improving operational EPB assessment by combining simulation-based methods with the normalisation of metered energy use. As demonstrated in this thesis, both analytical and machine learning approaches achieved good accuracy for weather normalisation. The degree-day method showed slightly lower accuracy, and the higher monthly percentage errors were likely caused by the use of degree-days alone, without accounting for solar radiation. Furthermore, the non-EPB energy and operational-hours adjustments based on metered energy remained conservative compared with the simulation-based methodology, while making the performance gap visible in comparison with the calculated EPC. These findings provide a better understanding of the energy performance of the analysed buildings.

Contribution to practice and policy

The results indicate the need for stable long-term policy signals, renovation incentives and improved knowledge about cost-optimal renovation measures. They provide practical input for renovation policy development, investment decision-making and future implementation of EPCs and MEPS.

The developed methods provide practical approaches for operational EPB assessment and are applicable to different building types, provided that the required metering data are available and the assessment assumptions are satisfied. They require a limited number of input parameters from building energy meters and stakeholders while enabling more accurate and policy-relevant assessment of non-residential building energy performance. The degree-day method provides a practical and sufficiently accurate solution when only monthly data are available. When applying this method, it is recommended that monthly percentage errors of the predictions are reported alongside the energy savings assessment to provide transparency regarding the uncertainty of the results.

The formalised and reproducible procedures for separating non-EPB energy use us-

ing tenant-level metering and adjusting for operational-hours variability using metered data have been incorporated into an additional calculation procedure within the existing national energy performance assessment methodology. This represents a documented policy outcome of the research and provides a basis for more credible EPCs and future implementation of MEPS under the EPBD framework. Their uptake by assessors and effects on assessment outcomes across the building stock remain to be evaluated.

5.4 Limitations and future research

This thesis has several limitations that should be considered when interpreting the results. The market-based renovation analysis was based on a sample of Estonian educational, office, grocery and hardware store buildings and reflects the regulatory framework, climate conditions and commercial real-estate market characteristics prevailing in Estonia; therefore, the findings may not be directly transferable to other countries. The renovation and cost-optimality analyses relied on reference buildings, calibrated simulation models, energy audits and stakeholder interviews, which inevitably include uncertainties related to future energy prices, investment costs, occupant behaviour, weather conditions, equipment performance and financial assumptions. The normalisation methods were developed and validated using a limited number of reference buildings and assumed the availability of sufficiently detailed metering, operational schedules and building information. In practice, such data may not always be available, which can limit the applicability and accuracy of the methods. The non-EPB energy separation procedure depends on the representativeness of tenant-meter data and assumptions regarding end-use allocation, while the operational-hours adjustment assumes that occupancy schedules and power loads adequately represent actual building operation. The operational-hours adjustment for heating energy use should be further refined, as simplified normalisation does not fully capture the dynamic thermal behaviour of buildings. The weather-normalisation and baseline-generation studies were validated primarily with measured and simulated data from a small number of non-residential buildings, and therefore additional validation across a wider range of building types, climates and operational conditions is required. Finally, although the proposed methods improve the comparability of metered-energy-based EPC assessment, they do not eliminate all uncertainty associated with occupant behaviour, tenant activities, future changes in building use, or the inherent limitations of simulation-based performance assessment. Future research should focus on improving calculated EPC methodologies and occupancy-profile assumptions, and integrating building automation and large-scale metered datasets into operational EPC assessment.

This thesis demonstrated that credible operational energy performance assessment of non-residential buildings requires measured energy use to be normalised for weather, non-EPB energy use and operational hours. The developed methods improve comparability between buildings and provide a practical basis for future operational EPC and MEPS implementation while simultaneously revealing the economic challenges that continue to limit NZEB renovation in commercial real estate.

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Abstract

Operational Energy Performance Assessment Methods for Credible Energy Certificates Based on Metered Energy in Non-Residential Buildings

To move towards climate neutrality, it is first necessary to know how efficient buildings are today. In addition, progress towards energy efficiency must be measured both at building level, using baseline values or thresholds, and at national and international scales, using consistent energy performance of buildings (EPB) assessment methods. Approximately ten Member States in the EU, including Estonia, calculate operational energy performance certificates (EPCs) using metered data. However, metered energy use is affected not only by the building and its technical systems, but also by weather, tenant activities, non-regulated energy uses and operational schedules.

This thesis aimed to investigate current energy use and renovation practices in non-residential buildings in Estonia and to develop approaches for metered-energy-based EPB assessment to improve the comparability of EPCs for non-residential buildings. The work is based on Estonian commercial and public building case studies, measured energy data, stakeholder interviews, calibrated energy simulation models, and statistical and data-driven normalisation methods.

The results show that current market-based renovation of commercial buildings is not sufficient to reach nearly zero energy building (NZEB) major renovation targets. Renovations improved energy performance only marginally, leaving commercial buildings approximately 40–50 % above the NZEB target. The main obstacles were the long 20–30-year payback time and the uncertainty of measures required for major renovation. This increases investment risk for real estate companies, which typically prefer a maximum payback time of 10 years. To start the NZEB renovation, building owners recommended the introduction of new energy or carbon taxes together with incentives and knowledge about energy-efficient renovation.

Energy renovation measures and savings needed to improve energy performance to the NZEB level were identified in a reference office building. The improvement of lighting, air handling units (AHUs), heating control, installation of a 69 kW photovoltaic (PV) system, and window replacement were needed to achieve the target. Reaching the NZEB renovation level was technically possible, but not attractive due to the long payback time, and is therefore unlikely to be implemented without renovation incentives.

In parallel with improving commercial buildings' energy efficiency, reliable quantification of renovation impact and the energy performance gap is essential for understanding the actual state of the building or building stock.

Weather conditions have a significant impact on measured energy use, which must therefore be normalised before metered energy data can be used for EPB assessment. This thesis developed and validated weather normalisation methods for ventilation heating energy use and post-retrofit baseline generation. The results of ventilation heating normalisation show that, in some cases, the heating degree-day (HDD) method may be a more practical solution, provided that an appropriate base temperature is used and operational hours are taken into account, as both significantly influence the results. For post-retrofit energy baseline generation, both degree-day and machine learning methods achieved acceptable accuracy, but machine learning models showed lower uncertainty and better monthly prediction performance.

This thesis proposes and validates two methods to normalise metered energy data. These methods address (i) non-EPB energy use by utilising monthly data from tenant

electricity meters, and (ii) variations in operational hours based on hourly data from main meters. The use of tenant meters helped overcome the common problem that non-EPB energy use is often not measured separately. Using this method, remarkable reductions in primary energy, in some cases more than 50%, are shown. Operational-hours adjustment in a building with longer use reduced primary energy by 14.0% for electricity and 10.1% for heating. Validation with detailed dynamic simulation models indicates that normalised results remained slightly conservative and made the performance gap visible when compared with the calculated EPC. Therefore, the proposed methods proved to be robust and reliable for both non-EPB energy reduction and operational-hours adjustment when applied to the case studies. However, the results show that operational-hours adjustment for heating energy use should be further refined, as simplified normalisation does not fully capture the dynamic thermal behaviour of buildings.

This thesis demonstrates the significant impact of non-EPB energy use, extended operational hours, and weather conditions on the energy performance of non-residential buildings and on the resulting assessment outcomes. The results show that the proposed normalisation methods can be applied with sufficient accuracy for operational EPB assessment.

Lühikokkuvõte
Mitteeluhoonete mõõdetud energiakasutusel põhineva energiamärgise hindamise meetodid

Kliimaneutraalsuse suunas liikumiseks on esmalt vaja teada, kui energiatõhusad on hooned praegu. Lisaks tuleb energiatõhususe poole liikumist mõõta nii hoone tasandil, kasutades lähteväärtusi või piirväärtusi, kui ka riiklikul ja rahvusvahelisel tasandil, kasutades ühtseid hoonete energiatõhususe (EPB) hindamismeetodeid. Ligikaudu kümme ELi liikmesriiki, sealhulgas Eesti, arvutavad kasutusaegset energiamärgist, Eestis kaalutud energiaerikasutust (KEK), mõõdetud energiaandmete põhjal. Mõõdetud energiakasutust ei mõjuta siiski üksnes hoone ja selle tehnosüsteemid, vaid ka ilmastik, üürnike tegevus, reguleerimata energiakasutus ja kasutusgraafikud.

Doktoritöö eesmärk oli uurida Eesti mitteeluhoonete praegust energiakasutust ja renoveerimispraktikat ning arendada edasi mõõdetud energiakasutusel põhinevat energiamärgise hindamise meetodit, et parandada mitteeluhoonete energiamärgiste võrreldavust. Töö põhineb Eesti äri- ja avalike hoonete juhtumiuuringutel, mõõdetud energiaandmetel, huvirühmade intervjuudel, kalibreeritud energiasimulatsioonimudelitel ning statistilistel ja andmepõhistel normaliseerimismeetoditel.

Tulemused näitavad, et ärihoonete praegune turupõhine renoveerimine ei ole piisav saavutamaks oluliselt rekonstrueeritava hoone energiatõhususarvu piirväärtust (C-klass). Renoveerimine parandas energiatõhusust vaid vähesel määral ning pärast turupõhist renoveerimist jäi KEK 40-50 % üle C-klassi piiri. Peamised takistused olid oluliseks rekonstrueerimiseks vajalike meetmete pikk tasuvusaeg (20-30 aastat) ning ebakindlus meetmete energiatõhususe ja sellest tuleneva säästu hindamisel. See suurendab kinnisvaraettevõtete investeerimisriski, kuna nad eelistavad tavaliselt kuni 10-aastast tasuvusaega. Energiatõhusama renoveerimise käivitamiseks soovitasid hooneomanikud kehtestada uued energia- või süsinikumaksud koos toetuste ning energiatõhusa renoveerimisega seotud teadmiste suurendamisega.

C-klassi saavutamiseks vajalikke energiatõhususmeetmeid ja energiasäästu hinnati ühe büroohoone näitel. Eesmärgi saavutamiseks oli vajalik valgustuse, ventilatsiooniseadmete ja kütte juhtimise parandamine, 69 kW päikesepaneelide süsteemi paigaldamine ning akende vahetamine. C-klassi saavutamine oli tehniliselt võimalik, kuid pika tasuvusaja tõttu majanduslikult väheatraktiivne ning seetõttu ei ole selle rakendamine tõenäoline ilma renoveerimistoetusteta.

Paralleelselt mitteeluhoonete energiatõhususe parandamisega on oluline hinnata usaldusväärselt renoveerimise mõju ja hoonete energiatõhusust, et mõista hoone või hoonefondi tegelikku seisundit.

Ilmastikutingimused mõjutavad mõõdetud energiakasutust oluliselt ning seetõttu tuleb tarbimine enne säästu arvutamist või energiatõhususe hindamist normaliseerida. Doktoritöös töötati välja ja valideeriti ilmastiku normaliseerimise meetodid ventilatsiooni kütteenergia kasutuse ning renoveerimisjärgse energiakasutuse baasjoone määramiseks. Ventilatsiooni kütteenergia normaliseerimise tulemused näitavad, et mõnel juhul võib kraadpäevade meetod olla praktilisem lahendus, eeldusel et kasutatakse sobivat tasakaalutemperatuuri ja arvestatakse kasutusaegadega, kuna mõlemad mõjutavad tulemusi oluliselt. Renoveerimisjärgse energiakasutuse baasjoone määramisel saavutasid nii kraadpäevade meetod kui ka masinõppemeetodid vajaliku täpsuse. Masinõppemudelid näitasid aga väiksemat määramatust ja paremat ennustuse täpsust kuupõhiselt.

Doktoritöös pakutakse välja ja valideeritakse kahte meetodit mõõdetud energiaandmete normaliseerimiseks. Need meetodid käsitlevad: (i) energiaarvutuses arvesse mit-

tevõetavat energiakasutust, kasutades üürnike elektriarvestite kuiseid andmeid, ning (ii) tüüpilisele kasutusele taandamist, kasutades peaarvestite tunnipõhiseid andmeid. Üürnike arvestite kasutamine aitas lahendada levinud probleemi, et energiaarvutuses arvesse mittevõetav (protsessienergia) energiakasutus ei ole sageli eraldi mõõdetud. Selle meetodi abil saavutati märkimisväärne primaarenergia vähenemine, mõnel juhul üle 50%. Pikema kasutusajaga hoones vähendas tüüpilisele kasutusele taandamine primaarenergiat elektri puhul 14,0 % ja kütte puhul 10,1 %. Dünaamiliste energiasimulatsioonimudelitega tehtud valideerimine näitas, et normaliseeritud tulemused jäid konservatiivseks ja näitasid olemasoleva hoone energiatõhususarvu erinevust võrreldes arvutusliku energiamärgisega (ETA). Seetõttu osutusid pakutud meetodid töökindlaks ja usaldusväärseks nii energiaarvutuses arvesse mittevõetava energiakasutuse taandamise kui ka tüüpilisele kasutusele taandamise seisukohast. Kütteenergia tüüpilisele kasutusele taandamise puhul näitavad tulemused aga olulist ebatäpsust, kuna lihtsustatud meetod ei võta arvesse hoone soojuslikku käitumist ning seega vajab kütteenergia tüüpilisele kasutusele taandamine edasist uurimist.

Doktoritöö näitab energiaarvutuses arvesse mittevõetava energiakasutuse, pikendatud kasutusaegade ja ilmastikutingimuste olulist mõju mitteeluhoonete energiatõhususe hindamisele. Tulemused näitavad, et pakutud normaliseerimismeetodeid saab piisava täpsusega rakendada mõõdetud energiakasutusel põhineva energiamärgise arvutamise jaoks.

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Market based renovation solutions in non-residential buildings – Why commercial buildings are not renovated to NZEB

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ABSTRACT

Renovation of commercial buildings was studied to analyze typical energy improvements and to determine the performance gap in relation to major NZEB level renovation. To provide input for Estonian long-term renovation strategy, building samples and interviews were used to study how the commercial property companies deal with the building renovation need in Estonia. Results show that in office buildings renovations improved energy performance marginally and a performance gap of about 40% existed after market-based renovation. About one third of trade buildings reached the NZEB level, but within the rest, the performance gap was about 50%. A common renovation cost was around 10 €/m^2, but major renovation will need 130–150 €/m^2. The main obstacle was the long, 20–30-year payback time and uncertainty of the measures for major renovation. This increases the risk of investment for a real estate company preferring max 10-year payback time. Interviewees pointed out, that tenants are not motivated to invest because the expected 2–3% saving in the sum of rental and energy cost seems invisible. To start the NZEB renovation, building owners recommended preparation of new energy or carbon taxes together with incentives and knowledge about energy efficient renovation.

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1. Introduction

1.1. Major renovation by 2050 in EU building stock

The building stock is responsible for approximately 36% of all CO_2 emissions in the European Union (EU). Therefore, to work towards the climate neutrality, the European Parliament disclosed an energy performance (EP) of buildings directive (EPBD) 2018/844/EU [1] for amending the directives 2010/31/EU [2] and 2012/27/EU [3]. The goal of these directives is to develop a sustainable, competitive, secure and decarbonised energy system in the EU Member States by 2050. Further steps are to develop measures that reduce the final energy use of buildings to reach the main goal of reducing greenhouse gas emissions in the Union by 80–95 % compared to 1990. Therefore, the Member States established the long-term strategies mobilising investment in the renovation of residential and commercial buildings.

This study has contributed to Estonian long-term renovation strategy [4] by providing input regarding renovation in commercial buildings such as office and trade buildings (hardware and grocery store). Non-residential buildings account for 25% of the total area of building stock in Europe. Trade buildings (28%) are the biggest category and office buildings (23%) are the second biggest in non-residential building stock. However, the specific energy use of non-residential buildings (covering all end-uses) is at least 40% greater than equivalent value for the residential sector. Over 20 years, electricity use has increased significantly due to the growth of IT equipment, data centers (increased also by the low technology of appliances industry) and air conditioning [5,6]. Stensson has found that in shopping malls, the energy use is dominated by tenant related electricity (mainly lighting) and cooling related energy (mainly resulting from heat loads from lighting, appliances and people) [7]. In grocery stores, the refrigeration has great impact on electricity use and will be responsible for 50–60% of electricity use [8,9].

Energy use of a building is evaluated with the energy performance certificate (EPC) that indicates the EP of a building calculated by a methodology adopted in accordance with Directive 2010/31/EU [2] and in Estonia defined as primary energy (PE). The change in [1] directs to use ISO 52000-1 [10], where the electricity used on-site for appliances (small power plug loads), commercial activities, elevators is not included in calculations, because they are outside the EPBD scope and not regulated (so-

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called non-EPBD electricity uses). In the Estonian regulation [11], appliances are included to energy calculations (later named as non-EPBD appliances), but elevators and other commercial activities are excluded. Therefore, today major electricity uses in commercial buildings, as also shown by the results of this study, are not necessarily considered by long-term renovation strategies.

1.2. Energy use in commercial buildings

The Estonian long-term renovation strategy [4] states that annual PE use (based on measured consumption data) in the building stock constructed before 2000 is 225–270 kWh/m^2 (delivered heating 130 kWh/m^2 and electricity 70 kWh/m^2) in office buildings and 332–360 kWh/m^2 (delivered heating 80 kWh/m^2 and electricity 140 kWh/m^2) in trade buildings. More detailed data is available from a Norwegian study [12] on five low and normal energy use office buildings where the annual energy use of different office buildings varies from 73 kWh/m^2 to 140 kWh/m^2 delivered electricity and from 33 kWh/m^2 to 153 kWh/m^2 delivered heat. The server room electricity (extra energy and cooling) was found for one office building to be 30% of total electricity use. A Swedish study on randomly chosen 94 trade buildings [8] concluded, that in retail premises, the total average PE was 256 kWh/m^2 and the electricity part from that was 172 kWh/m^2 (electric heating not included). The dominant heating source was district heating with the annual heating energy use of 67 kWh/m^2. The biggest part of electricity use was for lighting (42%), next for food cooling and fans respectively 26% and 12%. The exception is the grocery store where refrigeration consumes 145 kWh/m^2, then lighting 90 kWh/m^2 and fans 24 kWh/m^2. In comparison, in other stores, lighting was dominant with 59 kWh/m^2.

These data differ from the NZEB level. It is estimated that after the renovation to the NZEB level in Estonia, the PE for an office building should be 136–160 kWh/m^2 (delivered heating 70 kWh/m^2, electricity 45 kWh/m^2) and for a trade building 206–225 kWh/m^2 (delivered heating 55 kWh/m^2, electricity 85 kWh/m^2) [4]. Stensson's study addressing the best EP for the shopping malls shows that a great potential to reduce the total energy use exists even there, but it is recommended to apply appropriate incentives in this case [7].

1.3. The gaps between sustainability and market-based investment

The energy renovation need in the Estonian commercial building market is 17 million m^2 of total floor area to achieve the goal by 2050. Today's major renovation market is four times smaller than it should be to achieve the goal of the strategy [4]. Hinnells et al. show that the energy costs are usually less than 5% of the cost of operating a building [13]. REHVA states in the Guidebook [14] that in a traditional building the rent could be 300 €/m^2 (without value-added tax (VAT)), including maintenance of 10 €/m^2, and energy for 20 €/m^2 annually. Therefore, the energy composes only 6% of the total cost of the rent, making the potential of energy saving not very visible for a tenant.

Energy retrofit results have different types of uncertainty, like unpredictable weather data, building envelope thermal properties, installation efficiency, energy use, occupant behavior or financial and economic parameters (energy prices or discount/growth rates). Therefore, uncertainty can increase the cost of capital for energy efficiency investments and needs to be considered in financial analysis [15,16].

Several studies have reported, that many barriers exist in the commercial building renovation market. For example, barriers frequently highlighted are: knowledge about the real EP in building, inefficient certification system, uncertainty of return of investment and how organizations develop best practices of energy management [17–19]. Furthermore, Stensson found out [7] that less than half of the energy audits for shopping malls included cost-optimal energy efficiency measures. Therefore, it is essential to research more the areas over cost-optimal measures and building energy efficiency, including metering and control systems with sensors and real-time monitoring. Furthermore, the study [13] points out that leases can be used to set environmental performance targets and promote green issues.

Gohardani et al. [20] carried out 10 interviews with different stakeholders in Denmark that confirm these barriers. In addition, it was found that the EPC of a building is not a motivator for energy renovations because it is primarily based on the calculated energy use, which might substantially deviate from measured energy use. In general, according to their findings, the most important factors considered for sustainable renovation are the durability and building physics, which are affected by maintenance, deterioration and moisture.

1.4. General research concept

This study aims address the situation prevailing in the energy use and renovation of commercial buildings in Estonia and to find out the performance gap after market-based renovation to major NZEB level renovation, as required in the EPBD [3]. Building samples and interviews were used to study how the commercial property (real estate) companies deal with the renovation need in their buildings in Estonia. Specific objectives were:

- to quantify EP before renovation and after common market-based renovation;
- to identify the scope and cost of deeper renovation measures to achieve major NZEB level renovation;
- to interview the stakeholders to acquire an understanding why they are overlooking renovation to NZEB;
- to provide input for the development of NZEB renovation incentives of commercial buildings.

In this study, we cover office buildings, grocery stores and hardware stores described with building samples. Measured energy data was used to quantify before the renovation condition. After renovation (as conducted by building owners), either measured data or savings calculated with energy audit methods were used. Renovation costs were collected and calculated for a wider set of measures than used in the market-based renovation in order to analyze NZEB renovation cost and barriers. Therefore, in our study, we selected the buildings, analyzed the energy performance and savings that building owners had already executed. Further analyses were conducted for NZEB renovation measures and cost. HVAC improvement or replacement and lighting related measures were the main ones under investigation in this study. External insulation measure was not included, because this is cost inefficient renovation measure [21] and will be the last solution considered in commercial buildings. Finally, the survey among real estate companies was conducted to analyze their motivation and decision logic for renovation of commercial buildings.

2. Materials and methods

This section describes the boundary conditions and methods used in this study.

The limits of EPC classes in Estonia are shown in Table 1. In Estonian regulations, class C is the NZEB limit for major renovation of existing buildings [22]. EPC class C is also the target of Estonian Long-Term Renovation strategy and therefore it was used as a target of renovation in this study.

Table 1
Primary energy limits of Energy Performance Certificate Class in Estonia (EPBD scope without appliances).

Class	Trade, kWh/m^2	Trade EPBD scope, kWh/m^2	Office, kWh/m^2	Office EPBD scope, kWh/m^2
A[1]	160	154	100	62
B	190	184	130	92
C[2]	**230**	**224**	**160**	**122**
D	280	274	210	172
E	330	324	260	222
F	390	384	320	182
G	460	454	400	362
H	>460	>454	>400	>362

[1] NZEB for a new building.
[2] NZEB for major renovation.



Fig. 1. Examples of the grocery (a), hardware store (b) and office building (c).

Table 2
Floor area, floors and construction year of sample buildings.

Building	A_{HEAT}, m^2			No of Floors	Construction year
	Average	MIN	MAX		
Hardware	3858	1213	12,402	1, **2**, 4	2001–2012
Grocery	2653	210	11,015	**1**, 2	1936–2015
Office	12,760	8363	16,990	5–13	1952–2012

2.1. The sample of buildings and system description

Commercial building sample included in this study consisted of 6 office buildings, 22 grocery stores and 11 hardware stores that are actively in use, constantly maintained, have good or modern ventilation system and indoor climate is acceptable. Office buildings often represent a mixed use with some services and trade functions. The selection criteria for buildings were the availability of energy audits and energy improvement measures already implemented or planned that enabled preparation of detailed design documentation and budget. Typical examples representing each category of buildings are shown in Fig. 1.

The average heated (net floor) area (A_{HEAT}) of grocery stores is about 30% smaller than hardware stores area and the office buildings A_{HEAT} is almost 5x larger than that of grocery stores (Table 2). This has some impact on the renovation cost and energy savings to be taken into consideration throughout the next discussion. The most common floor number is marked in bold.

2.1.1. Description of HVAC systems

In hardware stores, air heating with ventilation supply air was used as a standard solution. In grocery stores, mainly underfloor heating and additionally radiators were used to heat a small amount of office and auxiliary rooms. Supplementary, the condenser heat from refrigerator has been mainly used in the extra heater of AHU, in some cases, for the DHW or underfloor heating. In office buildings (blds.), typically, the heating system with water radiators was the case.

Typical schematic diagrams of HVAC systems are shown in Fig. 2 and described in more detail in Table 3. The most common system options are marked in bold.

2.2. Calculation of actual energy performance in commercial building

Under some conditions, the measured energy performance (EP) may not provide data with the same resolution as the calculated EP; moreover, the availability of specific energy data depends on the installed metering device. Therefore, this case was analyzed because EPBD will consider assumed (standard) conditions, but offices and stores have also an EP that is not under the EPBD scope. We collected the data of delivered energy in reference buildings from energy invoices measured by main energy meters, so specific services were not measured. The used data was collected also by system administration and from in-

situ monitoring. Building design documentation, including renovation solutions and budgets, was also collected and used for the analyses.

The delivered energy of hardware stores has been taken as the average of years 2015–2017, for grocery stores data from years 2017–2018 and, office building from 2005 to 2017. Measured electricity data included all types of uses, as well as server room, cold room, industrial kitchen equipment and electrical equipment (e.g., elevators, outdoor lighting). Regarding ISO 52000–1 [10], some calculation procedures allow identification of the partial EP for specific services without a dedicated meter. Therefore, total measured electricity energy was divided to relevant end uses by energy balance calculations. The energy use under the EPBD scope, non-EPDB appliances and non-EPBD refrigeration electricity use was estimated based on Estonian regulations [11,22], Swedish [8] and Norwegian [12] studies (Fig. 3). The other non-EPBD electricity use

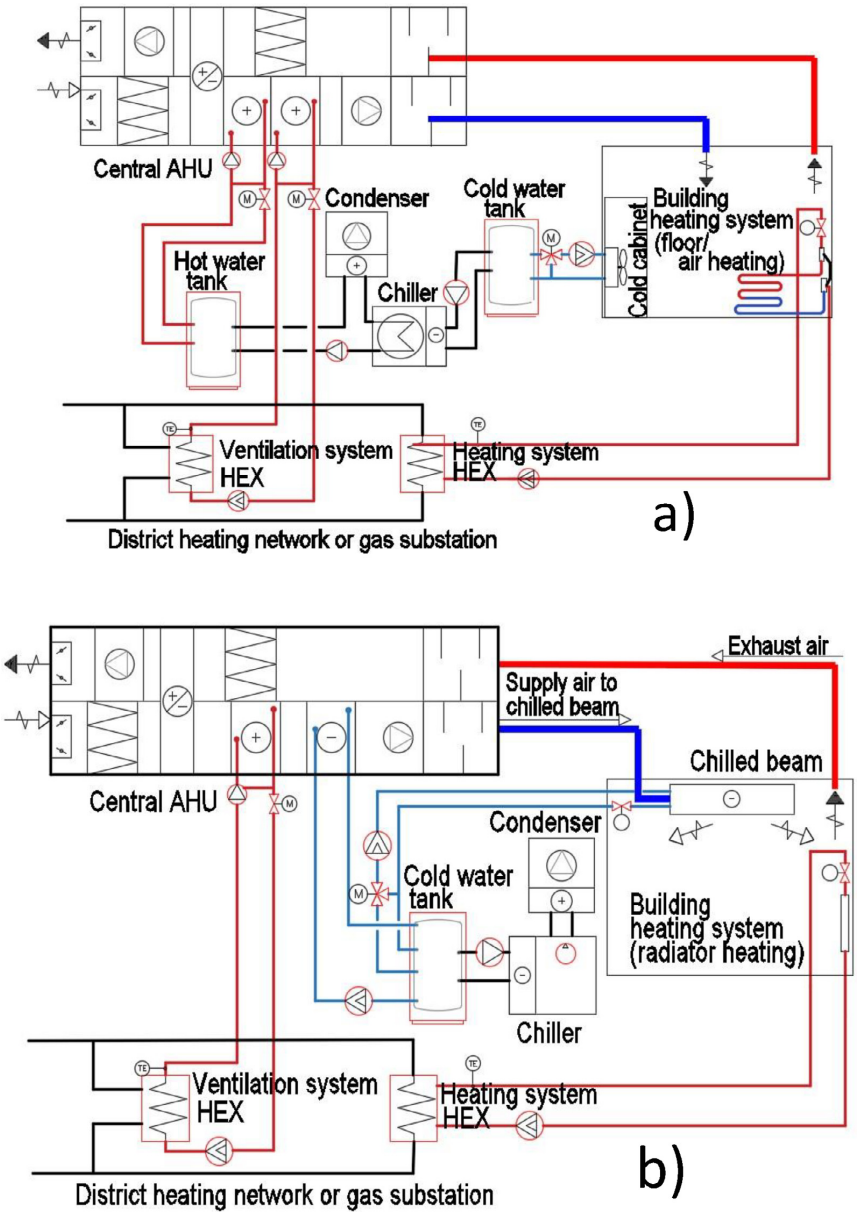


Fig. 2. Schematic HVAC system in trade (a) and office (b) buildings.

Table 3
The HVAC, refrigeration and lighting system options in each building (bld.) type.

System		Hardware	Grocery	Office
Main heating system		Floor heating	None	12
	None			
	Ventilation[1]	2	5	1
	Air heating[2]	8	1	None
	Radiators	None	6	5
	Electricity	1	None	None
Additional heating system		Heating air curtains in entrance, ventilation, radiators	Radiators, condenser heat, curtains, ventilation and electrical heater	ventilation, air curtains
Condenser heat from refrigerator		None	17	None
Cooling		**None**(1 bld. uses ventilation air cooling)	**Mainly for refrigerators**, in 4 blds. also SPLIT system for server rooms and offices,and 5 blds. will use ventilation air for cooling	**Ventilation and active beams**.+ 2 blds. use Fan Coils.+ 1 bld. uses cooling conv. integr. with susp. ceiling
Ventilation		**7 with rotary heat exchangers** (1 with recirculation).5 without heat recovery (1 with recirculation, 1 with VAV)	**16 with heat exchangers** (4 with VAV and recirculation, in 6 blds. the system does not work); 4 without heat recovery and 4 are with natural ventilation	**All buildings with rotary heat exchanger.** + some rooms are served with plate heat exchangers or run-around heat exchanger
Lighting		**Mainly LED**5 fluorescents (replaced to LED), 1 with both (50/50%)	**19 with fluorescent**. 5 with LED	**Fluorescent**
non-EPBD systems		–	refrigerator, cold room, industrial kitchen, outdoor lighting	server rooms, kitchen, control center, outdoor lighting

[1] Ventilation supply air heating in the air handling unit.
[2] Air heating with fan coils in the space.

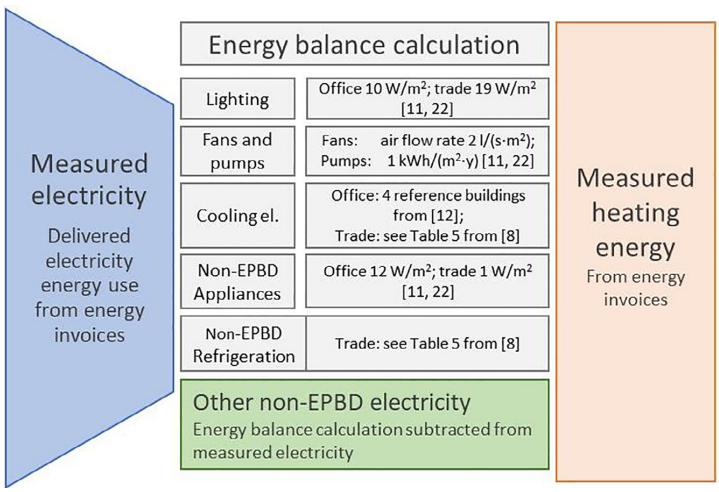


Fig. 3. Methods used in the study to divide the total measured electricity to end uses.

were obtained when the sum of EPBD uses, non-EPBD appliances and refrigeration electricity was subtracted from the total electricity use.

Lighting and appliances were estimated from the Estonian regulation standard use specification for internal heat gains (equal to electricity use). Fluorescent or similar lamps are assumed in commercial buildings. The power includes rated and starter power, i.e., 25% of the rated power. In addition, the usage profile of office buildings was 7:00–18:00 and five days per week, and for trade buildings, 7:00–21:00 and seven days per week. The calculation of comfort cooling electricity and refrigeration of grocery stores was estimated as shown in Table 4, by the percentage of specific electricity use of [8]. Food cooling was set to 45% for the buildings with electric heating, and without electric heating to 47%. For office buildings, some reference building data was used to evaluate the contribution of the cooling system [12]. This was based on five reference office buildings, including one reference building from Estonia. The average cooling energy use (space and ventilation supply air cooling) over these office buildings was 18 kWh/m^2 a and the SEER = 3.5 (for compressor type chiller) was taken from Estonian regulation [11]. With these data and assumptions, the electricity use for cooling resulted in 5.2 kWh/m^2.

For the calculation of the EP of HVAC aux, the AHU and the ventilation system were considered to start 1 h before and end 1 h after the usage time. In the calculation of office building AHU energy based on the Estonian regulation [22], it is assumed that

Table 4
The electricity energy use of grocery and hardware store from [8].

kWh/m^2, (A_{HEAT})	Foods		Other trade	
Electric heating incl. heat pumps	12.1	4%	5.2	5%
Comfort cooling	**3.8**	**1%**	**5.8**	**5%**
Pumps	11.7	4%	3.7	3%
Fans	23.9	7%	19.1	17%
Other real estate assets	9	3%	2.1	2%
Food cooling	**144.5**	**45%**	**8.4**	**7%**
Lighting	89.5	28%	58.7	51%
Other operating income	19.7	6%	9.1	8%
Remaining item	6.9	2%	2.3	2%
Total	321.1	100%	114.4	100%

the air flow rate is 2 l/(s × m^2) and the average specific fan power (SFP) for AHU is between 2.0 and 2.7 kW/(m^3/s), as these buildings are built about 10–15 years ago. This results in the annual electricity energy use of the office building AHU fans of 16.0 kWh/m^2, about 24 and 32 kWh/m^2 for grocery and hardware store respectively.

2.3. Evaluation of the market-based commercial building renovation in Estonia

In this study, the EPC/PE was calculated in basis of Estonian regulations [11,22], but we used actually measured specific heating and electricity energy use of buildings from what, the extra electricity use was excluded to evaluate the energy use corresponding to the standard use. Hereinafter, this outcome is named as energy performance (EP) before renovation.

Office building server room electricity (extra electricity and cooling electricity) was assumed to be 30% [12] and other extra electricity about 10% of total electricity. For the latter one, the energy use of the elevator and outdoor lighting in one of the sampled office buildings was estimated. Hardware stores were considered as without extra energy use. From grocery store electricity use, the refrigeration electricity has been excluded for 47% (or 45% with electric heating) to calculate EPC or PE use.

Estonian primary energy (non-renewable) factors (Table 5) from the regulation [22] was used in EPC/PE calculations.

The energy savings of each energy efficiency measures were estimated with energy audit calculation methods regarding to Estonian regulation [24]. Savings of all measures for each building was merged and subtracted from the EP before renovation. Finally, the second PE value was calculated to evaluate the level that the buildings will achieve after market-based renovation.

2.4. Evaluation of the acceptable renovation cost for real estate companies

In line with savings, the investment of each measure was estimated individually with the Total Concept method [25]. This method focuses on achieving maximum energy saving in the building within the profitability frames set by the building owner, who carries out the investment. The profitability indicator is the internal rate of return set by the building owner. Furthermore, the preconditions of the Total Concept method are:

- the investment of measures has to satisfy the request of the real estate company;
- the evaluation of the investment and savings has to be reliable;
- measures have to remain or improve the quality and indoor climate of the building;
- the savings have to be the largest possible.

It was considered that all these measures will be implemented in the same action package (done all together); thus, the design and construction work will be lower.

The energy savings were multiplied with energy prices for heating and electricity, to calculate the annual energy cost saving. Then the payback time was calculated. The package of measures was formed by arranging the different energy efficiency measures after the payback time.

For comparison, we estimated the necessary investment and possible annual savings for major renovation to the NZEB level. First, the EPC limit value (C-class) was subtracted from the PE after market-based renovation. The result was multiplied with the percentage of energy source (electricity or heating) and divided by the primary energy factor. The result was the annual energy saving in kWh/m^2 a. Additional investment needed for further renovation was acquired by subtracting the market-based measures investment from the total investment for the major NZEB renovation (specified in the Introduction). The energy prices were taken from the energy invoices of three building types and are in Table 6.

The limits of the internal rate of return (IRR) used for the IRR graphics were calculated over 20 years and considering the inflation rate of 2%; it means that the real internal rate of return (IRR_R) after one year is 17.6% if IRR = 20%. Therefore, the present value (PV) discount rate (below the dividing line in Eq. (1)) over 20 years for three IRR values is as follows: IRR 20% – 25.8; IRR 5% – 1.79; IRR 0% – 0.67. The PV discount rate was used to calculate the net present value (NPV). The calculated NPV set to 0 in 20 years and the investment (€/m^2) were used in Excel Solver function to calculate the annual saving (€/m^2) of a specific IRR. In this study, all the prices are without the value-added tax (VAT).

$$0 = NPV = \sum_{t=1}^{T} \frac{C_t}{(1 + IRR_R)^t} - C_0 \quad (1)$$

Table 5
Estonian primary energy factors.

Energy source	Factor, [-]
Efficient District heating[1]	0.65
Natural gas	1.0
Fuel oil	1.0
Electricity	2.0

[1] district heating system using at least 50% renewable energy, 50% waste heat, 75% cogenerated heat or 50% of a combination of such energy and heat [23].

Table 6
Energy prices for grocery, hardware store and office building.

Energy source	Grocery store	Hardware store	Office building
District heat, €/kWh	0.052	0.050	0.050
Natural gas, €/kWh	0.046	0.032	0.034
Electricity, €/kWh	0.072	0.087	0.095

where C_t is the energy annual cost during year *t;* C_0 is the initial investment cost for the measure and, IRR_R is calculated with Eq. (2), where *f* is the inflation rate,

$$IRR_R = \frac{1+\frac{IRR}{100}}{1+\frac{f}{100}} - 1 \quad (2)$$

2.5. Interview of building owners

Face-to-face structured interviews were conducted with building owners to ask how and why they renovate buildings. In total, six real estate companies, and two representatives from Estonian Association of Construction Entrepreneurs, representing main contractors, participated in the study. Structured interviews included three main themes:

1. Renovation logic in the market context
2. Motivation (or no motivation) to uptake the NZEB level energy renovation
5. Main problems and solutions

3. Results and discussion

3.1. Energy performance in buildings before market-based renovation

Measured EP of selected trade and office buildings is shown in Figs. 4, 5 and 6. All energy use components, both covered and not by EPBD, are included. It can be seen that the non-EPBD appliances (small power plug loads) and other non-EPBD electricity account for a substantial part of energy use in commercial buildings.

In the hardware store (HS), the electricity for lighting is the highest electricity component in most of the buildings, Fig. 4. Non-EPBD electricity shows large variation and is as high as 40–47% in buildings HS6, HS7, HS8 and HS12. This is explained by electric heating or some other facility electricity. In another half of buildings, non-EPBD electricity forms around 20–30% of energy use.

Buildings HS1 and HS2 serve as the reference for the EPC C-class, having PE of 214 and 231 kWh/m^2 respectively.

Total energy use of the grocery store (GS) (Fig. 5) is high because of non-EPBD refrigerator energy use. Building GS12 shows exceptionally high energy use resulting from higher frequency of technological equipment such as refrigerator and cold storage room, and also heating air curtains and a large window-to-wall ratio. Another outlier is GS18, where radiator heating has no thermostats and the frequency of the refrigerator is higher per heated area. If take out the refrigeration electricity use (47%), buildings GS1, GS14 and GS19 have the PE of 270–297 kWh/m^2, that is closer to the C-class than for other blds.

In office buildings (OB) (Fig. 6), non-EPBD electricity dominates (47–77%) because of elevators, server rooms, kitchens and appliances that are excluded from the EPBD scope. The high outgoing temperature of the heating system results the high heating energy need of OB5 and OB6. None of the office buildings will achieve the C-class, but buildings OB1 and OB2 are the closest with the PE of 207 kWh/m^2, which is by 40 kWh/m^2 more than that required for the C-class.

3.2. Market-based commercial building renovation in Estonia

The results of the market-based renovation of commercial buildings reveal that to achieve the C-class of EPC, savings from the implemented or suggested measures were insufficient. The EPC rating and PE use before and after market-based renovation is shown in Figs. 7 and 8 for office and trade buildings. The PE of office buildings has not changed significantly through market-based renovation – two of the analyzed buildings stay on the D-class and one on class E. Only in two buildings, EPC class increased to one step higher class and one of them is on the limit to reach two steps. PE reduced for these two 45 kWh/m^2 and 70 kWh/m^2.

The change of hardware store building EPC rating is more noticeable, i.e., previously only two hardware store buildings were on class C, but under market-based renovation, three buildings achieved C or B-class with PE 180–225 kWh/m^2. One hardware store building, that was on E-class before, achieved A-class after renovation by replacing the fluorescent lighting to LED and

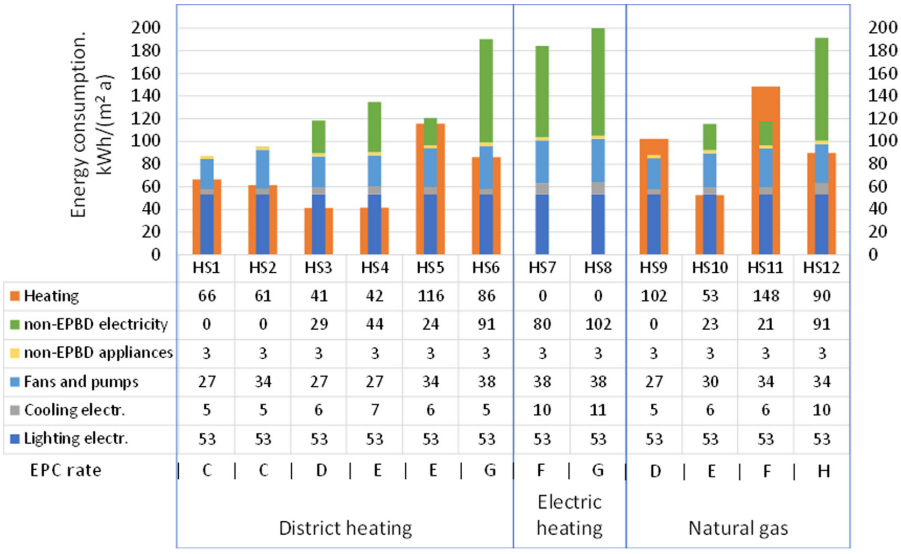
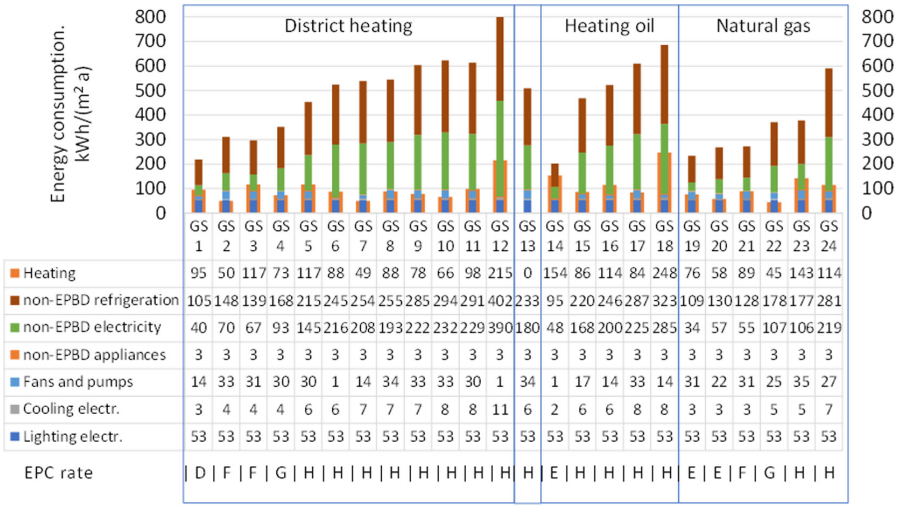
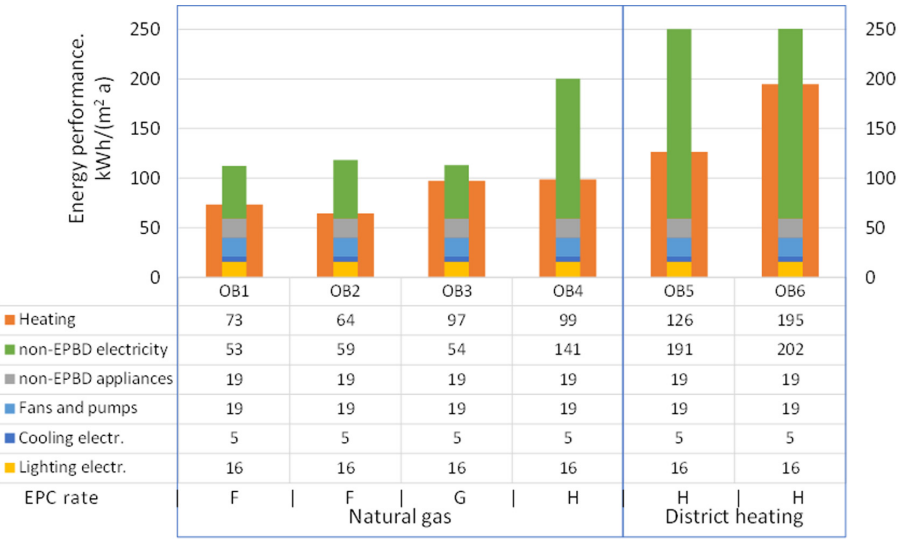


Fig. 4. Delivered energy of hardware store – sequence according to the energy performance certificate of total energy use.



	GS 1	GS 2	GS 3	GS 4	GS 5	GS 6	GS 7	GS 8	GS 9	GS 10	GS 11	GS 12	GS 13	GS 14	GS 15	GS 16	GS 17	GS 18	GS 19	GS 20	GS 21	GS 22	GS 23	GS 24
Heating	95	50	117	73	117	88	49	88	78	66	98	215	0	154	86	114	84	248	76	58	89	45	143	114
non-EPBD refrigeration	105	148	139	168	215	245	254	255	285	294	291	402	233	95	220	246	287	323	109	130	128	178	177	281
non-EPBD electricity	40	70	67	93	145	216	208	193	222	232	229	390	180	48	168	200	225	285	34	57	55	107	106	219
non-EPBD appliances	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
Fans and pumps	14	33	31	30	30	1	14	34	33	33	30	1	34	1	17	14	33	14	31	22	31	25	35	27
Cooling electr.	3	4	4	4	6	6	7	7	7	8	8	11	6	2	6	6	8	8	3	3	3	5	5	7
Lighting electr.	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53	53
EPC rate	D	F	F	G	H	H	H	H	H	H	H	H	H	E	H	H	H	H	E	E	F	G	H	H

Fig. 5. Delivered energy of the grocery store – sequence according to the energy performance certificate of total energy use (GS13 is with electric heating).



	OB1	OB2	OB3	OB4	OB5	OB6
Heating	73	64	97	99	126	195
non-EPBD electricity	53	59	54	141	191	202
non-EPBD appliances	19	19	19	19	19	19
Fans and pumps	19	19	19	19	19	19
Cooling electr.	5	5	5	5	5	5
Lighting electr.	16	16	16	16	16	16
EPC rate	F	F	G	H	H	H
	Natural gas				District heating	

Fig. 6. Delivered energy of office buildings – sequence according to the energy performance certificate of total energy use.

improving the building automatics, but the saving is too big, so its unlikely. However, about 65% of hardware stores will not achieve the C-class. Fig. 8b) shows, that only one grocery store achieved EPC from E to C-class with 222 kWh/m^2, and one class D. Other buildings are in classes E to H.

The measures with the investment per heated floor area presented in Table 7 include all of those implemented or suggested in energy audits, i.e., representing the level of the market-based renovation. These measures have been selected because of good payback time, as shown in Fig. 9 where the most used measures are compared to the payback time. Some differences in investments (e.g., measure No 3) are derived from the variation of average heated area (A_{HEAT}). However, bigger changes come from the extent of installations, which vary in each building.

Regarding the cost effectiveness, in the grocery store, the modernization of building automatics (No 1) and better lighting (No 2) have had best payback times and therefore often recommended to companies. Also, changing the heating or ventilation system (No 5) has good payback time, but the majority of these buildings already have HVAC systems that need no replacement. Measure No 4 was mainly suggested because of the aged old system and measure No 6 for one grocery store because there is no insulation on outer wall of the building.

In the hardware store, only three renovation measures were considered. The modernization of building automation (No 1) and changing the ventilation system to demand controlled ventilation (DCV) (No 3) were the main measures used in the hardware store. Measure No 1 was the most used, because it needs less effort

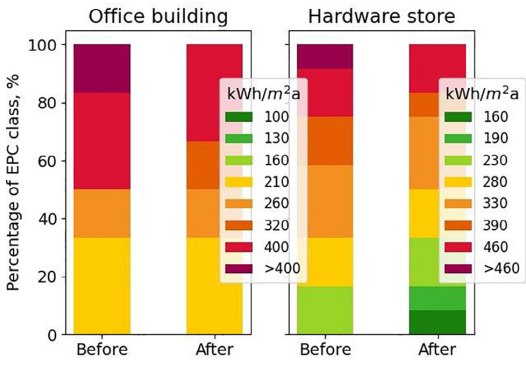


Fig. 7. The percentage of EPC rating before and after market-based renovation in the office and hardware store building (kWh/m^2 a shows the limit of EPC value).

and remote monitoring achieves good energy efficiency with low investment.

In the office building (Fig. 9), the most recommended measures are DCV or ventilation automation renovation (No 3) and improvement of HVAC control (No 7). Also, improving the lighting from fluorescent to LED (No 2) was often used. Measures Nos 8, 9 and 10, were used only, at a special need, e.g., in case of an old system, the improvement of which was cost-optimal, the renovation of cooling/heating system (etc. replacing the constant flow 3-way control valve to variable flow 2-way control valve) and the system balancing was done. The installation of the solar protect film was proposed in case of complaints about glare or overheating.

As an additional method, PV-panels and CHP plants were used for on-site energy generation, however rarely because of big investment needs. The average investment of PV-panels installation for grocery stores was about 290 000 € (max payback time 12.9 years). One case for the office building was 46 000 € with the payback time of 14 years. In energy savings, this was a good solution for grocery stores because average decrease of EPC was as high as 128 kWh/m^2 year. On the other hand, none of these companies used these solutions because of longer payback time. Further, buildings with steel profiled sheet roofs (as usual for trade buildings) would need structural reinforcement works to install the PV-panels to the roof for strengthening of the roof construction.

3.3. Convenient renovation costs to real estate today in Estonia

Fig. 10 show the gap in between the objective to achieve major NZEB level renovation and the actual performance of the market today. The comparison is based on the internal rate of return (IRR) calculated from the combination of renovation measures. The bottom part of the graphic shows the IRR of market-based measures and the graph on the top shows the IRR to achieve the NZEB level.

In grocery store, the IRR of the combination of market-based renovation measures is under 20% only in one case. The investment of this grocery store increases because of natural ventilation, and the installation of heat recovery AHU needs high investment. Hardware stores have more cases, with the IRR under 20%, which is due to the higher investment, but similar energy saving of the measure. The landlords of hardware store buildings tend to invest more in the energy efficiency.

Fig. 10 shows that the IRR of market-based renovation is about 10% only in one office building. The reason is that the building dates back to 1952 and its systems will need replacement or major renovation. The IRR of other buildings (construction year > 1995) is close to 20% and higher. In conclusion, landlords had considered the renovations only when the IRR was over 20%; in some specific cases, 7% was still acceptable. This resulted in the market-based renovation that failed to achieve the NZEB level of major renovation. For the NZEB cost level, in the case of hardware store and office building, the IRR will be below 7% and, in some cases, under 0%. For grocery stores, the picture is different for half of the cases, as the IRR acceptable to landlords would be about 10–18%. For another half of the cases, it will be below 7%, which is not in landlords' interest anymore.

To achieve the major NZEB level renovation, the cost of the required combination of renovation measures would be 130–150 €/m^2 (Fig. 10). There are several improvement possibilities in addition to market-based renovation measures. For example, in the office building it is reasonable to change also the tenant area lighting to LED (not only corridor), so that the energy use for lighting is 6 W/m^2 and to add the motion control sensors for lighting to the corridor. Further, a modern AHU can be installed to improve heat exchange rate and SFP. Also, the improvement or replacement of old heating- and cooling system should be done to achieve the NZEB level. In the trade building, it is possible to use PV-panels on the roof because of sufficient free area. Therefore, additional structural reinforcement work is needed to strengthen the roof construction.

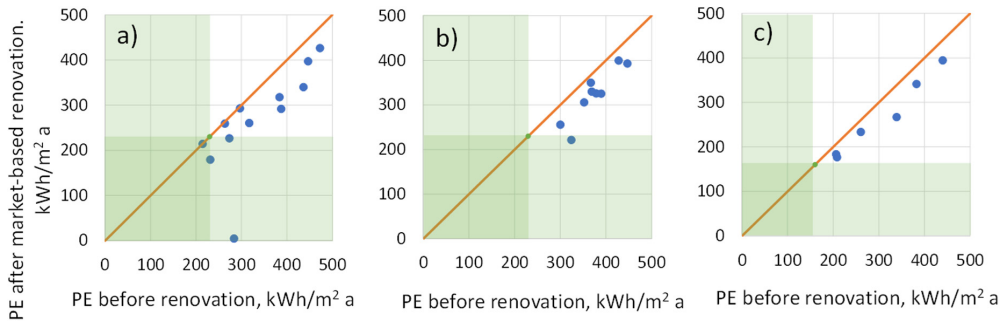


Fig. 8. The PE before and after market-based renovation of hardware (a), grocery (b) store and office building (c). The green area is the boundary of C-class and in grocery store 15 buildings are outside of graph. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 7
Energy efficiency improvement measures implemented in commercial buildings.

No	Measure	Description	Building	Investment, €/m^2
1	Building automatics	Renovation of bld. automatics, distance monitoring of HVAC systems	GS & HS	1.4 and 12
2	Better lighting	Fluorescent lighting replaced with LED, movement sensors installation. In office only to the corridor.	GS, HS and OB	5.7, 19 and 1.3
3	Demand controlled ventilation (DCV) or ventilation automatics	Placing the CO_2 sensors to the room, connecting it with AHU automatics; for office, also night setback and heat ex. cooling	HS and OB	5.3 and 0.6
4	Refrigeration renovation	Replacing the refrigeration and designing the condenser heat utilization in the heating system	GS	31
5	Larger renovation of HVAC systems	Changing the local heating source or ventilation system	GS	30
6	Building wall insulation	Installing thicker or more efficient insulation	GS	27
7	Improvement of HVAC control	Changing the control characteristics and automatics of HVAC systems	OB	0.4
8	Modernization of HVAC	Renovation of the AHU fans, heating/cooling coil, heat ex. or heating/cooling system and heating/ventilation system balancing	OB	0.4
9	Modernization of heat supply system	Renovation of heat supply system	OB	4.5
10	Installation of the solar protect film	Installing the solar window films	OB	6.7



Fig. 9. The usage of measures compared with the payback time of renovation in hardware, grocery store and office building.

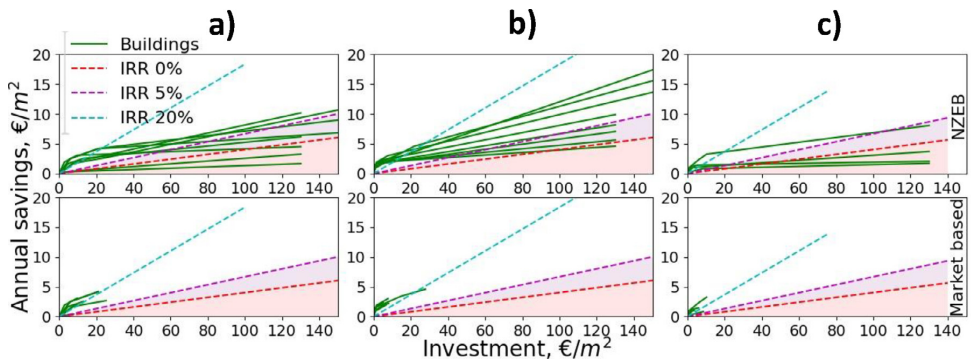


Fig. 10. The internal rate of return (IRR) for hardware (a), grocery (b) store and office (c) building renovation measures.

3.4. Results of interviews of real estate companies about renovation in building stock

In interviews with real estate companies, the objective was to discover the conditions that landlords of real estate will consider for the energy renovation. It was found that there are multiple barriers that block NZEB renovation in commercial non-residential buildings stock. To understand these barriers, the starting point is a rent and energy cost structure seen in Fig. 11. According to the estimation from Statistics Estonia [23] from years 1999–2009, over 10 years, the average rental price for tenants in Tallinn office buildings was 98 €/m^2 and in trade buildings 129 €/m^2 per year (on the basis of leases transactions intermediated by real estate companies in Estonia). The energy cost was 9–24 €/m^2 and 10–28 €/m^2 per year in the office and trade building respectively, calculated with data of Figs. 3, 4 and 5. Therefore, the average energy cost (11 €/m^2 in offices and 17 €/m^2 in hardware) is about 10–12% of the sum of rental and energy cost. The market-based renovation will reduce the average energy cost, but only about 1–3% for office building and hardware stores. NZEB renovation will

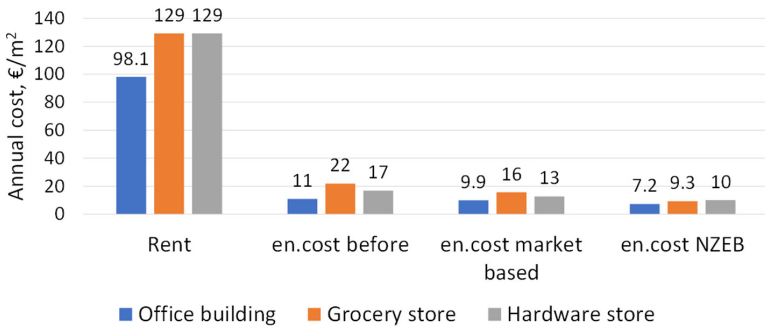


Fig. 11. Comparison of annual rent and energy cost for three reference buildings.

reduce 3–4%. The decrease for grocery stores is 4% and 8%, respectively. This benefit was seen quite marginal because it needs to be shared between the landlord and the tenant.

3.4.1. Renovation logic in the market context

In the Estonian real estate market, the common subjects involved in the business are: landlord (LL), investor (IN – usually the same as LL) and tenant (TE). LL owns and manage the building and rent the property to TE (for about 5–15 years). LL has the right to decide on the renovation, but TE pays the utility bills. To execute the energy renovation, LL will discuss the matter with TE and expects to share the investment. However, TEs are often not motivated to invest because of disruptions and a small share of energy costs in their cost structure. This case is usual for office buildings and rare for trade buildings. Moreover, LL has low motivation to invest if the rental price cannot be increased, which is seen as a common situation. In such cases, only TE will benefit from the renovation.

In the investment perspective, three cases can be distinguished:

1) Short-term investment – LL will purchase the real estate for a short period of 3–7 years and is not interested in the condition of the building in a long term.

2) Longer-term investment – LL will purchase the property for a longer period, but not much over 10 years.

3) Long-term investment – LL will purchase the property for a long period, e.g., 20–30 years.

In the first two cases, the LLs are not interested in renovation because they will sell the real estate before the building will need renovation. At the same time, the long-term investors are more interested in renovation because the technical systems will need upgrading every 30 years. This applies for trade buildings that are in the same investor's portfolio for a longer period.

Nevertheless, there are some positive aspects in the market. Investors that are not landlords are more likely to invest to real estate, that has a green certificate. Also, awareness about the green issues of the commercial building is increasing and therefore some LLs are already working to improve their real estate through complying with LEED and BREEAM. Furthermore, in a tenant view, some foreign companies will have green policy, so they are interested in energy performance and will encourage the LL to improve the building. Another stimulant is that the building technical systems will age over 30 years and tenants will complain if indoor climate conditions are insufficient, so the landlords are forced to renovate. However, today these last aspects are just seen as exceptions by interviewees.

3.4.2. No motivation to uptake NZEB level energy renovation

At the uptake of improvement works, motivation to upgrade to NZEB is not common on both sides because tenants will pay the energy bill. It was found that in the selection of rental space, TE will take a decision based first on the rental cost, furnishing and indoor climate, not energy bills. Therefore, LL is not motivated to do energy renovation because there is no demand from the market. Another remarkable barrier is the payback time. To achieve the NZEB level, the payback time will be about 20–40 years. Desired payback time for acceptable measures was not considered to exceed 10 years. Over 20 years is seen as far too much because banks give loans for a 15-year perspective. Payback time must be ultimately under 30 years because the HVAC systems need replacement every 30 years. Therefore, the interviews revealed a substantial conflict between EPBD cost optimality for 20 years payback period and the acceptable payback time of 10 years by LL.

LLs pointed out that it is difficult to estimate the NZEB investment risk, because there is high uncertainty of possible energy savings in the future. The reason is a lack of knowledge on energy efficiency and cost-optimal solutions because energy simulations are usually not conducted for renovation works. Also, a frequent change of EP regulations including primary energy factors and possible new requirements was seen as a factor adding uncertainty. Furthermore, in some cases, the building needs to be closed or partly closed during renovation, so LLs cannot ask the same rent or even worse, the tenant could leave because of noise or discomfort during the renovation period. Another aspect that LLs mentioned was that of builders' responsibility, which could be extended; thus, they could place more focus on the quality of the building.

In peripherical locations the situation is even worse. First, the problem is that tenants will not have many opportunities for rental, so they have to accept the conditions they have and therefore, LL is not motivated to make any effort. In periphery, the renovation cost is higher because of longer travel and transport distances, and the knowledge of energy efficiency is more deficient.

3.4.3. Main problems and solutions

Interviewees had a common consensus that the main problems are too long payback time of renovation for real estate companies and no demand for energy renovation from tenants.

One common solution, that interviewees pointed out was the need to prepare new taxes raising energy cost and stimulating to undertake renovation for building owners. To have an effect, with new taxes, incentives for energy efficient renovations should be introduced (no current renovation grants or other financial incentives for commercial buildings exist in Estonia). One proposed idea was to set an obligation to building owners, that they need to prove the EP of the building every 20 years. Furthermore, real estate companies prefer to be informed about changes in the regulations in advance for a longer period. They prefer to have better

defined and stable boundaries for the classification of EPC classes and primary energy factors. Today, energy regulations were seen to change so fast that it is difficult to estimate the investment risk of energy renovation.

Other solutions mentioned were to increase the knowledge about energy efficiency and renovation possibilities with the following ideas:

1) To develop detailed measures packages that ensure the building owner certainty to improve the EP and reduce the risk of investment. Probably, in case of a government grant for energy improvement measures, a company will accept a longer payback time of 12–15 years.

2) To set the incentive for building monitoring or audit, a real estate company will be offered more detailed awareness on the energy use of the building and energy efficiency solutions.

3) To provide more detailed energy audits in the perspective of finance, the fulfilment of future renovation measures and the social sustainability of building.

4) In general, to focus on remote monitoring and building automation, providing easy awareness about the building performance and energy use.

4. Conclusions

Studies of market-based renovation in commercial buildings are scarce; so are analyses of the barriers that prevent reduced energy use of buildings as needed for decreasing greenhouse gas emissions. Therefore, this study focused on the market-based renovation and how the commercial property companies deal with the renovation need in their buildings in Estonia. Building samples were used to estimate energy use and savings, and interviews with the representatives of real estate companies, to identify the market logic and the barriers of renovation.

Primary energy use after market-based renovation in over 65% of trade buildings was 30–197 kWh/m^2 and in all office buildings 17–234 kWh/m^2 over the NZEB level. In addition, it revealed that a substantial part of the measured energy use was out of the EPBD scope, i.e., representing unregulated uses not considered in the EPC/PE calculation. It was estimated that non-EPBD electricity uses could be about 20% in the hardware store, will reach to 80% in the grocery stores (refrigeration 47% and other non-EPBD electricity 33%) and 50–70% in the office buildings. This makes current energy savings on the office and trade building renovation marginal relative to the goal of EPBD.

Selection of market-based renovation measures was found strongly correlated to the payback time. The most used (60–80%) measure in trade buildings was the modernization of building automation with average payback time of 1 year for grocery stores and 10 years for hardware stores, and in office buildings, the demand-controlled ventilation or ventilation automation renovation with an average payback time of 2 years.

The convenient renovation cost to real estate companies in Estonia was only about 10 €/m^2 and the internal rate of return (IRR) of measure package around 20%. This is far from the investment of the renovation package to the NZEB level of about 130-150€/m^2 and the IRR below 10%.

Interviewees emphasized the problem that renovation to NZEB has too long payback time. Another essential problem was lack of motivation of tenants to share the investment because of small share of the energy cost. For a tenant, the average rental price was 98–129 €/m^2 in Tallinn, and energy cost 11, 17 and 22 €/m^2, respectively in the office building, hardware and grocery store. Therefore, the energy cost was about 10–12%, market-based renovation resulted in 1–3% and NZEB renovation would result in 3–4% cost saving in the sum of the rental and energy cost in office buildings and hardware stores. Savings were somewhat better in grocery stores, where market-based renovation resulted in 4% and NZEB renovation would result in 8% saving.

To solve the problem, interviewees recommended to prepare new energy or carbon taxes together with incentives for energy efficient renovations. Knowledge development about cost-optimal measures was seen also important to control the risks to renovate to NZEB. Furthermore, real estate companies prefer to know about the change of regulations in advance for a longer period and more stable boundaries to estimate the risk of investment.

In conclusion, this study enabled us to describe typical market-based renovation measures and to show the reason why commercial buildings are not renovated to NZEB. The results can be utilized to develop incentives and taxes needed to achieve the NZEB level. Further investigations should consider the cost-optimal measures for renovation of existing buildings to the NZEB level, which are currently non-existent in practice.

CRediT authorship contribution statement

Helena Kuivjõgi: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing - original draft, Writing - review & editing, Visualization. **Aivar Uutar:** Conceptualization, Data curation, Supervision. **Kalle Kuusk:** Conceptualization, Formal analysis, Investigation, Project administration. **Martin Thalfeldt:** Conceptualization, Supervision, Funding acquisition. **Jarek Kurnitski:** Conceptualization, Methodology, Writing - review & editing, Supervision, Project administration, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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NZEB and market-based renovation case study of an existing office building

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Abstract. The goal of decarbonizing the building stock in the EU requires a multi-fold increase of the current renovation rates. In Estonia, the non-residential building sector has had little or no public support to improve the energy efficiency. Therefore, it is essential to study the energy efficient and cost-optimal measures for non-residential building renovation to give guidance to real estate companies and other stakeholders about the renovation alternatives. Furthermore, crucial is to provide input to the government to develop the renovation grant and incentives for renovation. In this study, energy renovation measures and savings to improve the energy performance to NZEB level were identified in a large (16 990 m^2 heated area) office building. For that purpose, energy use was measured, simulation model developed and calibrated, feasible and more comprehensive energy improvements and costs analysed. The improvement of lighting, AHU, heating, installation of a 69 kW PV system, and window replacement was needed to achieve the goal with a primary energy use of 163 kWh/m^2. However, some of the applied measures had long payback times of 40-70 years and are not realistic to be implemented without renovation incentives.

1 Introduction

European Union (EU) has a goal to develop a sustainable, competitive, secure, and decarbonised energy system in EU Member States by 2050. The purpose and guidelines are brought out in the energy performance (EP) of building directive (EPBD). [1]–[3] Further steps are to develop measures that reduce the final energy use of buildings to reduce greenhouse gas emissions. Non-residential buildings account for 25% (m^2) of the total stock in Europe and office buildings are the second biggest category (23%). However, the specific energy use of non-residential buildings (covering all end-uses) is at least 40% greater than the equivalent value for the residential sector. [4], [5]

Energy use of a building is evaluated with the energy performance certificate (EPC) that indicates the EP of a building calculated by a methodology adopted in accordance with Directive 2010/31/EU [3]. In Estonia it is defined as primary energy (PE) and the limits from [6] are in **Table 1**. Regarding the standard ISO 52000-1 [7], to calculate the PE use and EPC of an existing buildings, the measured energy use can be used. However, the electricity for other uses than energy performance of buildings (non-EPB) (e.g., small power plug loads, commercial activities, elevators, industrial kitchen) should be excluded from calculation. Nevertheless, in Estonian regulation [6], [8] the appliances are included to the energy calculation. Therefore, as shown in [4] and [11], today major electricity uses in the office are not necessarily considered by long-term renovation strategies.

Estonian long-term renovation strategy states that today the annual PE use is 225-270 kWh/m^2 (delivered heating 130 kWh/m^2 and electricity 70 kWh/m^2) in office buildings constructed before 2000. However, to achieve the major renovation NZEB level (class C in **Table 1**), the PE for an office building should be 136-160 kWh/m^2 (delivered heating 70 kWh/m^2, electricity 45 kWh/m^2). Unfortunately, today building stock has several barriers that prevent to achieve the NZEB level renovation. One main barrier is the long, 20-30 year payback time of NZEB renovation, as real estate companies prefer the payback time around 10 years. [9]

Table 1. Primary energy limits of Energy Performance Certificate level in Estonia (EPBD scope without appliances)

Class	Office, kWh/m^2	Office EPBD scope, kWh/m^2
A[1]	100	62
B	130	92
C[2]	160	122
D	210	172
E	260	222

[1]NZEB for a new building
[2]NZEB for major renovation

This study is a continuation and clarification of the article [9], that has contributed to Estonian long-term renovation strategy [11]. The idea is to give an overview of the measured energy consumption and analyse the energy renovation measures to improve the energy performance of NZEB major renovation in office buildings.

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2 Methods and materials

2.1 Reference building measured energy use

The reference building (**Figure 1**) is actively used, well maintained, and with good ventilation system 5 storey office building with heated area 16 990 m^2 built in 2008. The construction has a deep foundation and non-loadbearing exterior walls (EW) (wood frame with mineral wool thickness 0,15-0,18 m), external floor (EF) towards ambient air (concrete panel with wood frames and insulation thickness 0,25 m), EF towards the ground (concrete floor with insulation in perimeter), roof (load-bearing profile plate and mineral wool plates or concrete panel with 0,18 m mineral wool and 0,05 m EPS 65F). Building has an uncommon shape and WWR about 50%. We consider that the reference building has 3 elevators (one for each building section). On the first floor, the trade areas and canteen (respectively, 10% and 3% of the total area) are located, and the other floors are for offices (about 83% of the total area) and health care (5% of the total area). Heat supply comes from the local natural gas substation and electricity from the power grid.



Figure 1. Reference office building built in 2008 (AU Energiateenus)

We collected the delivered energy of the reference building from the energy invoices measured by the main energy meters (look in **Figure 2**). Measured total delivered heating energy was 104 kWh/m^2 and electricity 126 kWh/m^2 (non-EPB included). Specific services were not measured, but assumed by calculations and other studies. Domestic cold water use was measured and the domestic hot water (DHW) percentage of this was assumed to be 40%. Using this data, the DHW use was calculated by Equation 1:

$$Q_{DHW} = m \times C_p \times \rho \times \frac{\Delta T}{3600} \quad (1)$$

Where

E: energy, kWh
m: the mass of water, l
Cp: specific heat of water, kJ/kg °C
ΔT: temperature difference, °C
ρ - density of water in 50 °C

DHW use was separated from heating energy use and the last one was weather normalized with degree day method. **Table 2** shows the monthly weather normalized heating energy, domestic hot water (DHW) heating, and electricity energy use in the reference building in the years 2012-2014.

Table 2. Actual measured weather normalized energy use in the reference building

	Space and ventilation heat, kWh/m^2			DHW, kWh/m^2			Electricity, kWh/m^2		
Year / Month	2012	2013	2014	2012	2013	2014	2012	2013	2014
Jan	16.6	15.6	14.7	0.60	0.56	0.51	12.9	9.92	9.36
Feb	13.7	13.3	15.2	0.52	0.48	0.47	11.0	8.77	8.75
Mar	11.3	11.6	12.1	0.57	0.46	0.89	11.5	8.61	9.33
Apr	7.94	7.93	8.01	0.53	0.50	0.53	10.9	8.75	9.75
May	5.02	3.77	4.28	0.59	0.59	0.56	11.5	9.77	11.2
Jun	2.11	2.78	2.04	0.54	0.50	0.67	11.6	10.1	11.0
Jul	2.78	1.68	3.01	0.43	0.59	0.58	10.8	10.8	13.7
Aug	2.03	2.00	2.27	0.47	0.42	0.58	10.6	12.1	12.5
Sep	4.61	4.96	4.92	0.57	0.50	0.57	9.8	11.2	11.4
Oct	6.92	8.23	7.42	0.49	0.55	0.76	11.1	10.8	11.1
Nov	10.9	12.1	11.0	0.55	0.50	0.59	9.7	10.0	9.9
Dec	12.2	16.0	14.8	0.42	0.52	0.61	9.0	9.6	10.0

The specific electricity for non-EPB use (**Figure 2**) has been estimated by further calculations. Cooling electricity and plug load electricity for the server room has been calculated by the installed power of fan coils in server room. This building has 18 electrical service or server rooms that are cooled by fan coils with different cooling power: 1 kW to 4 kW. The sum of fan coil cooling power is about 61 kW and it was assumed that the servers will work every day all over the year (8760h). Annual cooling power is about 31 kWh/m^2. The SEER of chiller has been taken 3.5 and therefore, the electricity use is 9 kWh/m^2. Outdoor lighting is fluorescent lights with bulb power 58 W. As there are about 25 lights, the annual electricity energy for outdoor lighting was 6.2 MWh (0.36 kWh/m^2). The electricity of the 3 lifts was about 13 kWh/m^2, estimated by the study [12].

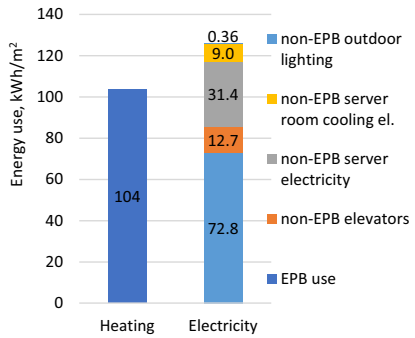


Figure 2. Energy use in the reference building

2.2 Energy simulation model

For further analyses, there was built an energy simulation model (further as the base model) of the reference building (**Figure 3**) in the energy and indoor climate simulation program IDA Indoor Climate and Energy 4.8 (IDA-ICE) by using project documentation and energy audit information. The test reference year of Estonia was used [13].

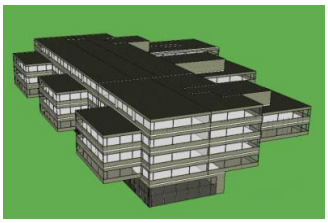


Figure 3. IDA-ICE model of the reference building

Table 3 represents the input data of the base model. In the calculation of heating energy use, the generation and distribution were considered with heat source efficiency factor and efficiency factor of the distribution and output of radiator (

Table 3). For cooling calculation, there was taken into account also the heat loss coefficient and Eq. 2 was used from [8].

$$Q_j = (1 + \beta_{je}) Q_{je} (1 + \beta_{rs}) Q_{rs} \qquad (2)$$

where

Q_{je} - annual net energy of AHU cooling elements kWh;

Q_{rs} - annual net energy of zone units kWh;

β_{je} – the energy loss associated with AHU cooling elements

β_{rs} - the energy loss of cooling energy distribution to zone

Base model imitates the real performance of the reference building and has occupancy, appliances, lighting, and AHU schedules according to real use (in Appendix 1, **Figure 9**-**Figure 14**).

Finally, the delivered energy has been correlated with primary energy factors as for natural gas 1.0 and for electricity 2.0 to calculate the PE.

Table 3. Input data of the base model and for energy use calculations

Occupants. m² per occupant	17
Equipment. W/m² (average, office/trade)	12/1
Lightning. W/m² (average, office/trade)	10/12
Temperature setpoint for heating. °C	21
Temperature setpoint for cooling. °C	24
Air flow rate. l/(s m²) (average)	1.7
Heating system (radiators) efficiency. -	0.97
Heat source (gas) efficiency. -	0.95
AHU fans SFP kW/(m³/s)	1.1-1.9
SEER of chiller. -	3.5
Ventilation heat exchanger efficiency, -	0.7/0.4
Annual DHW consumption. l/m²	103
Average U-value of model, W/(m²K)	0.38
SFP - specific fan power.	

2.3 Calibration method of energy simulation model

Energy simulation model has been calibrated with the corresponding and normalized energy use of the reference building (**Table 2**), both data for year 2014.

The calibration was done and the modelling uncertainty was controlled by the coefficient of variation of root mean square error (CV(RMSE)) Eq. 3, (regarding to ASHRAE Guideline [14]) which indicates the uncertainty inherent in the model and the computer model shall have a CV(RMSE) of 15% relative to the monthly calibration data. Results are in **Table 4**.

$$CVRMSE = 100 \times [\sum (y_i - \hat{y}_i)^2 / (n - p)]^{1/2} / \bar{y} \qquad (3)$$

The energy performance simulation in standard condition was done to calculate the energy performance certificate (EPC) and clarify whether the measures achieve the level of NZEB major renovation. The base model according to standard conditions uses the schedule in Appendix 1, **Figure 9**, every zone for occupancy, appliances and lighting (except in the trade area, where the lighting and appliances schedule is 0.55 at 7-21:00). The AHU works in full capacity from 6:00 to 19:00 and outside these hours is set to work 7.5% of the total capacity.

2.4 Improvement of energy performance

Several energy saving measures have already been implemented in this building. However, the improvement of automatics, rebuilding of the cooling system, improvement of free cooling of ventilation and cooling system did not achieve the NZEB level of this building regarding to energy audit. Furthermore, there has been constructed the combined heat and power (CHP) station and the photovoltaic (PV) panel system. Arithmetical calculation shows that these savings will achieve the C-level of this building, but needs further detailed investigation.

Table 4. Calibrated data and uncertainty of energy simulation model (measured and simulated results are for year 2014)

Measured, kWh/m²		Simulated, kWh/m²		RMSE		NMBE	
Heat.	Electr.	Heat.	Electr.	Heat.	Electr.	Heat.	Electr.
15.2	4.82	15.5	6.06	0.09	1.54	-0.30	-1.24
15.7	4.65	15.1	5.33	0.37	0.47	0.61	-0.68
13.0	4.80	11.9	5.77	1.10	0.95	1.05	-0.97
8.54	5.36	8.11	5.91	0.18	0.30	0.43	-0.55
4.84	6.63	5.80	6.61	0.92	0.00	-0.96	0.02
2.71	6.57	3.45	6.55	0.55	0.00	-0.74	0.01
3.59	9.12	1.41	8.32	4.76	0.64	2.18	0.80
2.85	7.97	2.50	7.04	0.12	0.87	0.35	0.93
5.48	6.98	3.74	6.05	3.05	0.88	1.75	0.94
8.17	6.59	7.79	6.09	0.15	0.24	0.39	0.49
11.6	5.48	12.8	5.48	1.41	0.00	-1.19	0.00
15.4	5.43	15.2	6.06	0.05	0.39	0.21	-0.62
			CV>	**12%**	**12%**	**3.8%**	**-0.9%**

This study was considering different measures to increase the energy use and achieve the C-level of the reference building. Several measures were selected by the suggestion of energy audits, the knowledge of the authors, and measures earlier studied in [9] were improved.

The measures were added to the base model individually (method described in **Figure 4**) and the saving of every measure has been calculated with the energy simulation software IDA-ICE 4.8.

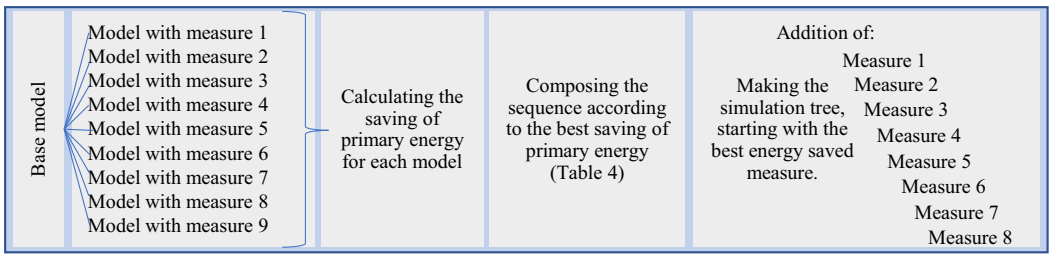


Figure 4. Methodology to compose the energy saving packages

Furthermore, the sequence of measures regarding the best saving of primary energy was composed and the models with measure packages were composed by adding each measure one by one to the model, so each package had one measure more than previous.

The costal savings and investment of each measure was estimated by calculations with data from project documentation and energy audits, and the experience of the authors of this study. The energy price has been taken from energy invoices in the years 2017-2018 as 0.031 €/kWh and 0.072 €/kWh, respectively, natural gas and electricity.

3 Results and discussion

Specific energy use for heating and electricity of the base model has brought out in **Figure 5**. The calculation of real use resulted the energy use of 113 kWh/m^2 and 75 kWh/m^2, respectively, for heating and electricity. This achieves the PE of 263 kWh/m^2. The calculation of standard use gives the heating energy 89 kWh/m^2 and electricity energy 56 kWh/m^2 that resulted PE 201 kWh/m^2 (D-level).

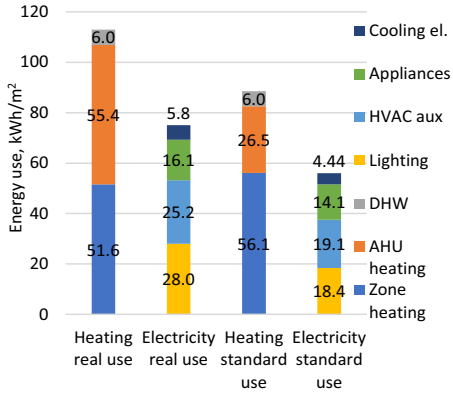
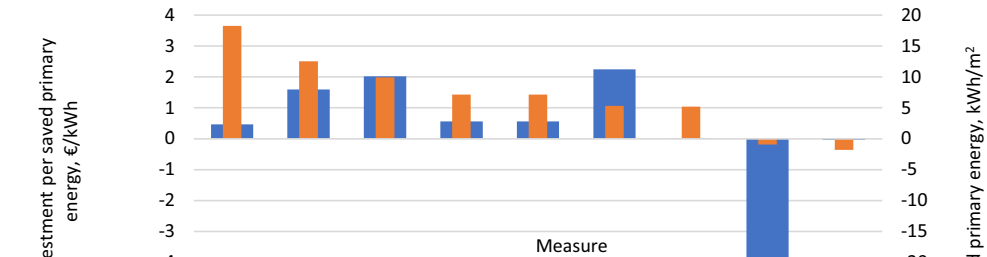


Figure 5. Heating and electricity use of the base model

Table 5. Individual measures implemented in the base model (the sequence is according to the highest saving in primary energy)

No	Measure description	Parameters		Delivered energy savings kWh/m^2		Annual costal savings, €/m^2		Invest-ment, €/m^2	Saved PE, kWh/m^2	€ per saved PE, €/kWh	Pay-back time, y
		Base model	After	Electr.	Heat.	Electr.	Heat.				
1	Improving the lighting	In trade area 12 W/m^2, office 10 W/m^2	In trade area 12 W/m^2, in office 6 W/m^2	11.4	-4.45	0.82	-0.14	8.52	18.3	0.47	12.5
2	Improvement of AHU fans SFP	SFP = 1.098-1.93 kW/(m^3/s)	SFP = 1-1.7 kW/(m^3/s)	6.25	0.01	0.45	0.00	20.0	12.5	1.60	44.4
3	Improvement of AHU heat exchanger	Efficiency: rotated hex. 70%; coil hex. 40%	Efficiency: rotated hex. 80%; coil hex. 60%	0.08	9.74	0.01	0.30	20.0	9.91	2.02	65.0
4	Adding the cooling effect to AHU heat exchanger	Heat exchanger is not working between 14 May and 31 August	Heat exchanger is working all the time	0.11	6.92	0.01	0.21	4.0	7.13	0.56	18.0
5	Change of canteens AHU ventilation control	CAV	VAV with CO_2 control and setpoints min 700, max 800	1.50	4.15	0.11	0.13	4.0	7.16	0.56	16.9
6	Changing the windows from 2-layer to 3-layer windows with better sun protection	Pilkington Suncool 66/33 (6C(66)-15Ar-4): g0.36, T0.33, T_{vis}0.66, U1.1	Pilkington Suncool 40/22 (6C(40)-15Ar-4-15Ar-S(3)4): g0.2, T0.17, T_{vis}0.36, U0.6	0.75	3.84	0.05	0.12	12.0	5.34	2.24	69.3
7	Night setback of indoor temperature	constant 21°C	6-20:00 set to 21°C; Other time set to 19°C	0.20	4.78	0.01	0.15	0.06	5.18	0.01	0.39
8	Sun protection film improving the windows shading	Shading parameters: g0.36, T0.33	Shading parameters: g0.20, T0.13	0.73	-2.41	0.05	-0.07	6.33	-0.94	-6.70	NA
9	Improvement of free cooling function [1]	Tamb <11°C Tsupply = 18°C; Tamb >11°C Tsupply = 16°C	Tamb <15°C Tsupply = 18°C; Tamb >15°C Tsupply = 16°C	-0.33	-1.14	-0.02	-0.04	0.06	-1.80	-0.04	NA
10	PV panels installation	No PV system	Installation of 230 panels with system power 69 kW	3.28	0	0.24	0.00	5.62	6.6	0.86	23.8

[1] Setpoint of supply air temperature (T_{supply}) was adjusted by ambient temperature (T_{amb})



	1	2	3	4	5	6	7	8	9
€ per saved PE kWh	0.47	1.60	2.02	0.56	0.56	2.24	0.01	-6.70	-0.04
Saved PE, kWh/m2	18.3	12.5	9.91	7.13	7.16	5.34	5.18	-0.94	-1.80

Figure 6. The investment and saved primary energy of individual measures

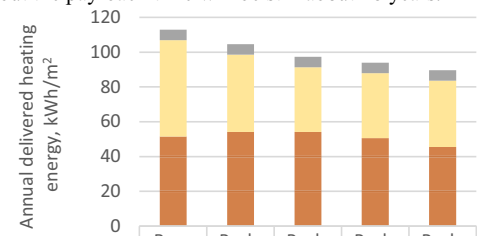
Furthermore, several renovation measures in **Table 5** were implemented in the base model and the energy savings were identified. The highest saving in primary energy was achieved by replacing the fluorescent lighting with LED – 18.6 kWh/m^2 annually. That was also the cheapest measure with 0.47 €/kWh saved primary energy and the shortest 12.5-year payback time. Measures 2 and 3 have bigger investment, because the improvement of AHU fans or heat exchanger separately still needs a replacement of the entire air handling unit that costs about 20 €/m^2. The payback time will be 26 years, if the measures are made together (AHU replaced with unit with better fans SFP and heat exchanger temperature efficiency). From **Figure 6** we can see that measures like sun protection film and improvement of free cooling function were less worth measures and in further analyses they are not involved. The installation of the PV-panel system was an additional measure to achieve NZEB level.

The energy simulations were done with the base model and models with the four following packages (pack.) with similar payback time:

- Package 1 – measures 1-4: pay-back time 32 years
- Package 2 – measures 1-5: pay-back time 30 years
- Package 3 – measures 1-6: pay-back time 34 years
- Package 4 – measures 1-7: pay-back time 32 years

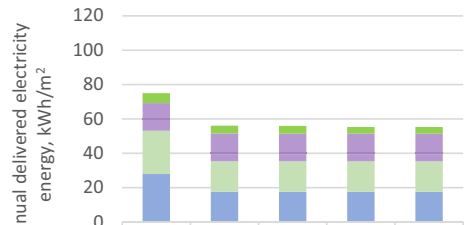
PV-panel (measure no 10) was later added to all packages. Previously mentioned, the base model had standard use PE 200 kWh/m^2 and EPC label D. Package 1 improved the electricity and heating energy considerably (**Figure 7**-**Figure 8**) - respectively, 19 kWh/m^2 and 8.4 kWh/m^2. However, the standard use PE is 173 kWh/m^2 that stays in EPC D-level. Further packages did not improve the electricity performance, but reduced the heating energy use considerably. Adding measure 5, the canteen AHU control with CO_2 sensors (package 2) reduced the heating energy for 7.2 kWh/m^2 and resulted the standard use PE 165 kWh/m^2, that is close to NZEB level. With package 3, after replacing the windows, the heating energy reduces for 3.5 kWh/m^2 and resulted in NZEB level with standard PE use 160 kWh/m^2. Using the night setback of indoor temperature in addition to previous measures (package 4) saved the heating energy for 4.3 kWh/m^2 and gave good PE use even without PV-panels - 163 kWh/m^2. Nevertheless, to achieve NZEB major renovation, the installation of PV panel system is essential.

The payback time of individual measures is high and will be over 40 years for half of measures. However, if measures are made as packages, the payback time is smaller, but still in between 30-34 years. Furthermore, replacing the window change measure with the night setback measure will reduce the investment of package 3, but the pay-back time will be still about 28 years.



	Base model	Pack. 1	Pack. 2	Pack. 3	Pack. 4
DHW	6.0	6.0	6.0	6.0	6.0
AHU heating	55.4	44.5	37.2	37.2	38.1
Zone heating	51.6	54.1	54.1	50.6	45.5

Figure 7. Annual delivered real heating energy for the base model and models with different renovation packages



	Base model	Pack. 1	Pack. 2	Pack. 3	Pack. 4
Cooling el.	5.8	4.5	4.5	3.9	3.9
Equipment	16.1	16.1	16.1	16.1	16.1
HVAC aux	25.2	17.7	17.7	17.7	17.7
Lighting	28.0	17.7	17.7	17.7	17.7

Figure 8. Annual delivered real electricity energy for the base model and models with different renovation packages

4 Conclusion

Analyse of energy efficiency and cost-optimal measures for non-residential building renovation is essential to achieve the goal and decrease greenhouse gas emissions. Therefore, this study focused on energy performance and renovation measures, citing one larger office building as an example. The measured energy consumption, the calibration method of energy simulation with energy consumption of the existing office building, and identification of energy renovation measures were the tools to discover the improvement of the energy performance to NZEB level of major renovation.

The cheapest measure, changing the lighting improved the electricity energy performance significantly and therefore, saved the primary energy for 18.6 kWh/m^2. In general, the majority of measures were with good primary energy saving (5-18 kWh/m^2), but at the same time with long payback time for real estate companies – over 16 years, and even will reach over 60 years. Using the measures together in renovation packages reduced the payback time to 30 years, that is still not suitable for real estate companies.

Authors found that replacing fluorescent lighting to LED, upgrading the AHU with a better performance unit, and improving the automatics, using night setback for heating and replacing windows will result the primary energy use close to the NZEB as 163 kWh/m^2. However, to reach this goal, the 69 kW photovoltaic panel system is needed.

The replacing of the windows in an office building is a big investment measure and will be under serious consideration, is it needed or not. Calculations show that replacing the window change measure with the night setback measure will result the PE use 161 kWh/m^2, that is almost NZEB level, but it needs further investigation with some more case studies.

The limitation of this study is the calibration method, as the measured data has been weather normalized, but the simulation were done with test reference year. Further studies need to be done to investigate the impact of this difference and to develop the calibration methodology.

This research was supported by the Estonian Centre of Excellence in Zero Energy and Resource Efficient Smart Buildings and Districts, ZEBE (grant 2014-2020.4.01.15-0016) funded by the European Regional Development Fund, by the European Commission through the H2020 project Finest Twins (grant No. 856602) and the Estonian Research Council grant (PSG409).

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Appendix 1

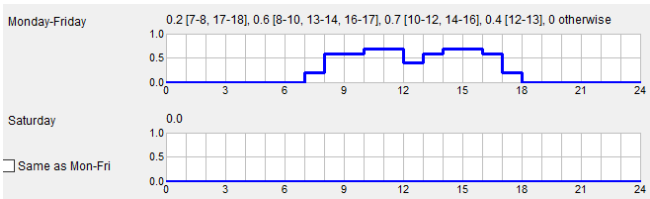


Figure 9. Schedule for occupants, equipment and lighting

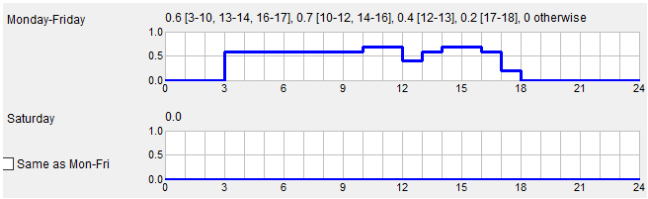


Figure 10. Schedule for C-building occupants, equipment and offices

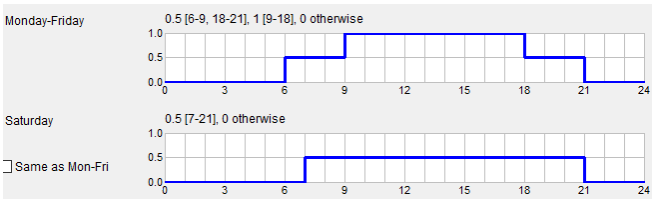


Figure 11. Schedule for AHU1

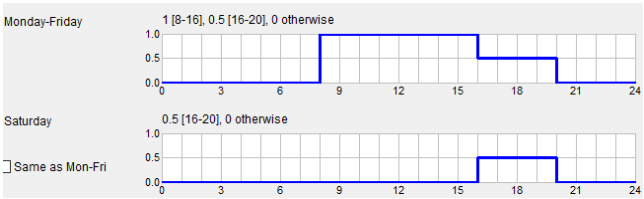


Figure 12. Schedule for AHU2 (canteen)

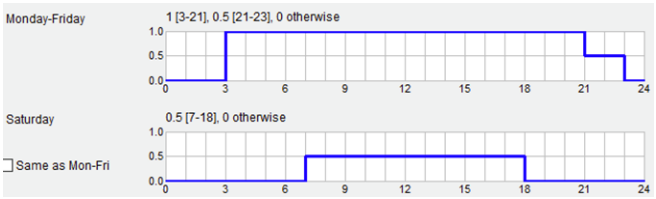


Figure 13. Schedule for AHU3 (C-building)

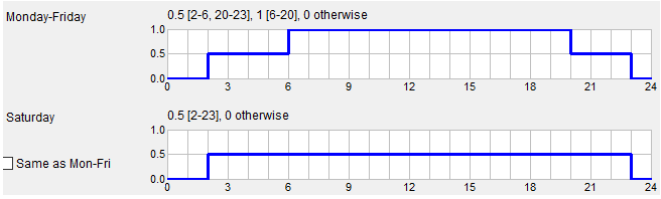


Figure 14. Schedule for AHU4

PUBLICATION III

H. Kuivjõgi, J. Laaneste, M. Thalfeldt, and J. Kurnitski. Heat recovery ventilation system heating energy weather normalization – calculation method and case study. *E3S Web Conf.*, 362:09003, 2022.

Heat recovery ventilation system heating energy weather normalization – calculation method and case study

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Abstract

Today, we have measured energy consumption or used data from utility bills and standard weather normalization methods (heating degree days (HDD)) to easily calculate the energy performance certificate (EPC) for existing building. However, normalization methods must be upgraded to be more accurate for weather. This study uses analytical model for weather normalization of air handling unit heating consumption. The models derived from measurements of the ventilation system in a real building were conducted and the normalization aspects were analysed. A new analytical weather normalization calculation method for ventilation heating is compared with heating degree day normalization.

Introduction

The weather normalization of metered energy use is important for energy labelling and comparison, as well as, to improve the energy performance of existing and future buildings. However, today there are few methods to weather normalize the energy performance of different building services. Dynamic simulation-based weather normalization will give us good accuracy. However, considering bigger scale weather normalization, it is slow method. For faster calculation we have heating degree day (HDD) method that can be done with easy calculation. Berggren et. al. used in their study the static and dynamic method for weather normalization of space heating. The static method is easier to use, and from a weather normalization perspective, it is as accurate as dynamic normalization. (Berggren and Wall 2017) Furthermore, C. Tam et al. proposed new HDD based method with weighting exponent. (Tam, Liao, and Poh 2021) Considering the HDD method, Meng and Mourshed show that the base temperature should be estimated carefully. (Meng and Mourshed 2017)

However, today, the HDD method is mainly used for space heating, but there are few studies about methods in particular for ventilation air heating weather normalization. This study will develop a new analytical model for weather normalization of heating consumption for the air handling unit with regenerative rotor heat exchanger. New method is compared with traditional HDD method and normalization aspects are analysed. The real capacity calculation that is calibrated with hourly measured ventilation heating and electricity energy data is used to imitate real AHU heater energy need.

Method

Reference building

The reference building was 3 046 m^2 school building built on 1980. The renovation was done on 2020 and new ventilation system was constructed with 11 air handling units (AHU) with heat recovery.

In this study, only one AHU with rotor heat exchanger is analysed. That will service one part of school building classrooms and will have high quality metered electricity and heating energy data from August 2020 to April 2022.



Figure 1: Reference building

Metered energy data, cleaning and preparation

The accumulative metered AHU heat coil heating and fans electricity energy data was obtained from energy meters hourly from August 2020 to April 2022. Data from 2021 was mainly used in this study. Electricity and heating power were calculated with subtracting the hourly metered energy consumption row by row. Outliers and errors in electricity power was made even with previous hour data. The operation rate of AHU heating coil was generated from electricity power. Equation 1 was used for the calculation of the operation time.

$$\tau_i = \sqrt[3]{\frac{\Phi_{el,i}}{\Phi_{el,max}}} \quad (1)$$

where τ_i is the operation rate in specific hour, $\Phi_{el,i}$ is electricity power (kW) in specific hour and $\Phi_{el,max}$ is

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the maximum electricity power (kW) during calculation period. During 8. May - 18. Nov the AHU heating coil operation rate was zero. (Figure 2)

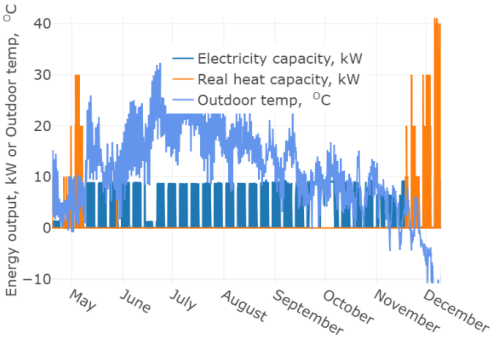


Figure 2: Comparison of heating and electricity power

AHU heater energy need calculation model

In this study, we used the AHU heater energy need calculation model that uses equations 2-6. The model takes hourly outdoor temperature data T_{out}, given parameters (Table 1), and will calculate the AHU heating coil heat output (power) in kW per every hour for one year. The ventilation air flow rate Q_v was multiplied with operation rate composed by real electrical data of AHU fans described previously. Fan temperature rise was set 0 K.

$$\Phi_v = \rho \cdot c \cdot \Delta T_h \cdot q_v \cdot \tau_i \quad (2)$$

where, ρ is the density of air 1.2 kg/m^3, c is the specific heat capacity of air 1.006 kJ/(kg·K), q_v is air flow rate m^3/s multiplied with AHU operation rate τ_i; ΔT_h is temperature difference the heater should cover:

$$\Delta T_h = \mathrm{MAX}\left(T_{supply} - T_{after,hx}, 0\right) \quad (3)$$

where, T_{supply} is supply air setpoint temperature in °C, and was considered as constant; $T_{after,hx}$ is the air temperature in °C after heat exchanger and calculated with equation:

$$T_{after,hx} = \eta_{hx,lim} \cdot (T_{extract} - T_{out}) + T_{out} \quad (4)$$

where, $T_{extract}$ is the extract temperature that is equal to room temperature in °C; T_{out} is the outdoor temperature in °C and $\eta_{hx,lim}$ is calculated:

$$\eta_{hx,lim} = \frac{T_{extract} - T_{exhaust}}{T_{extract} - T_{out}} \quad (5)$$

where, $T_{exhaust}$ is the temperature in °C after heat exchanger that is limited and was calculated with equation:

$$T_{exhaust} = \mathrm{MAX}(T_{extract} - \eta_{hx,const} \cdot (T_{extract} - T_{out}), T_{exhaust,lim}) \quad (6)$$

However, in this case, as the rotor did not significantly increase heating energy use despite outdoor temperatures below -30 °C, the $\eta_{hx,lim}$was always constant $\eta_{hx,const}$.

Air handling unit heat recovery and control parameters

Second part of this study was to detect the AHU heat recovery parameters that reference building will have (Table 1). The minimum exhaust temperature was taken as lowest temperature -30 °C, because we detected frost protection did not significantly increase heating energy use. However, the real heat exchanger heat recovery efficiency, extract and supply air temperature are not known and were detected by parameter optimization with minimizing the CV(RMSE) between real metered and AHU heating coil heat output calculated with Equation 2 (separately for Jan, Feb, Mar, Nov, Dec). Optimization was in limits: supply air temperature 16-21 °C, extract air temperature 22-24 °C and heat exchanger efficiency 0.75-0.9. The optimization was done with real operation rate described previously. Final parameters were generated by averaging optimized parameters of these months (Table 1).

Table 1: AHU parameters

Parameter	Abbreviation	Value
Minimum exhaust air temperature, °C	$T_{exhaust}$	-30
Extract air temperature, °C	$T_{extract}$	21.75
Ventilation air flow rate, l/s	q_v	4749
Supply air temperature, °C	T_{supply}	20.26
Heat recovery efficiency	$\eta_{hx,const}$	0.809

Analytical model for weather normalization with mean temperature (MT) and parameters

The model was composed by the difference in ventilation air heat capacity between real and test reference year (TRY) climate (Kalamees and Kurnitski 2006), where corrected ventilation air heat capacity is

$$\Phi_{h,corrected} = (\Phi_{\mathrm{h,real}} + \Delta\Phi_{\mathrm{h,TRY,Real}})^{+} \quad (7)$$

The difference was calculated with

$$\Delta\Phi_{\mathrm{TRY,Real}} = \rho \cdot c \cdot q_v \cdot \tau_i \cdot (\Phi_{h,Real} - \Phi_{h,TRY}) \quad (8)$$

, where

$$\Phi_{\mathrm{h,Real}} = \mathrm{T_{out,Real}} + \mathrm{MIN}\left(\mathrm{T_{extract}} - \mathrm{T_{exhaust,lim}}; \eta_{\mathrm{hx}} \cdot (\mathrm{T_{extract}} - \mathrm{T_{out,Real}})\right) \quad (9)$$

$$\Phi_{\mathrm{h,TRY}} = \mathrm{T_{out,TRY}} + \mathrm{MIN}(\mathrm{T_{extract}} - \mathrm{T_{exhaust,lim}}; \eta_{\mathrm{hx}} \cdot (\mathrm{T_{extract}} - \mathrm{T_{out,TRY}})) \quad (10)$$

where the $T_{out,Real}$ and $T_{out,TRY}$ are outdoor temperatures in every hour respectively in 2021 and in TRY. Other parameters are in Table 1.

Furthermore, the model will consider two limitations. First, the outdoor temperature was limited with the base temperature that is the outdoor temperature, when no heating is needed. This is calculated with the equation:

$$T_{out,lim} = \frac{T_{supply} - \eta_{hx} \cdot T_{extract}}{1 - \eta_{hx}} \quad (11)$$

The outdoor temperature was taken as minimum temperature between T_{out} and $T_{out,lim}$.

$$T_{out} = MIN(T_{out}, T_{out,lim}) \quad (12)$$

Secondly, the $\Phi_{v,corrected}$ was calculated only when the result is positive, otherwise the heating power is zero.

The AHU heat coil heating power of the TRY climate was calculated hourly with equations 1-5 and then aggregated daily, weekly, monthly and yearly.

Calculations and comparisons of two methods

The AHU heat consumption of the TRY climate was compared with two methods: mean temperature (MT) and HDD method. In the MT method, the corrected consumption was calculated with the daily, weekly, and monthly average outdoor temperature when AHU fans speed (operation rate) was over 54%. Secondly, the MT method was compared with HDD method. The base temperature (Tb) was identified with change-point method (Rohdin et al. 2018), where the linear regression line meets x-axis. Furthermore, the Tb was calculated for different boundary conditions, with Equation 11 or randomly selected (

Table 2). Thereafter, the R^2, CV(RMSE) and NMBE was calculated to identify the Tb that will have the best correlation for HDD normalized and TRY daily consumption.

HDD weather normalization was done by Equation 13, where Q_v is real AHU heating energy consumption and HDD is heating degree days in test reference year and real year. Calculations were performed from January to December 2021.

The comparison between two normalization methods was done with data, where operation rate was over 54%.

$$Q_{v,HDD,corrected} = Q_v \cdot \frac{HDD_{TRY,}}{HDD_{Real}} \quad (13)$$

The daily average outdoor temperature was calculated with two methods for HDD normalization:

1) All 24h outdoor temperature was included (except may-nov);
2) Outdoor temperature during fans minimum speed 54%;

Results and Discussion

Model uncertainty

The accumulative consumption of all year calculated with optimized parameters is compared with measured consumption in Figure 3 and Figure 4. The CV(RMSE), and R^2 of this comparison for hourly accumulative consumptions are in limits of model calibration (ANSI/ASHRAE 2002), respectively <30% and ≥75%. NMBE is 8% over the limit ±10 % (Figure 3).

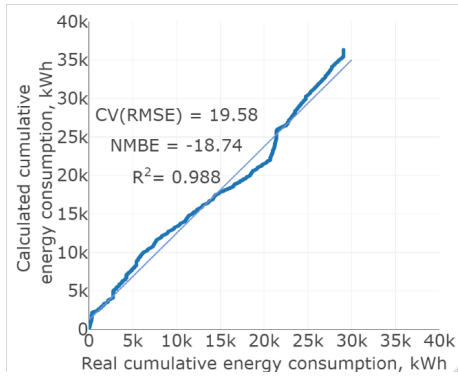


Figure 3: The accuracy of consumption calculated with optimized parameter

Base temperature for HDD normalization

Best fitting base temperature 14.4 °C was identified with cleaned datapoints during 2021 with minimum fan speed 54%. However, from

Table 2 can see that other data selection conditions had good correlation as well. The linear fitting of final base temperature is shown in Figure 5.

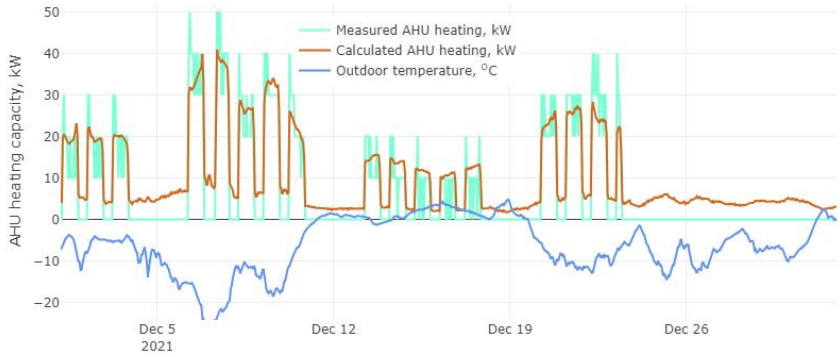


Figure 4: AHU real measured and model calculated energy consumption with outdoor air temperature in December

Table 2: The identification of base temperature of AHU heater

Tb	R^2	CV(RMSE)	NMBE	Tb calculation method	Boundary conditions for datapoint selection
11.0	0.987	16.63	-0.27	random selection	-
12.9	0.996	8.70	1.40	Linear fitting	All datapoints during Aug. 2020-2021
13.1	0.996	8.79	1.47	Linear fitting	cleaned datapoints during 2020-2021 (may-nov is removed)
13.3	0.996	8.91	1.50	Calculated eq. 11	optimized parameters in Table 1
14.4	**0.997**	**8.82**	**1.42**	Linear fitting	cleaned datapoints during 2021 with minimum fan speed 54%
15.1	0.994	11.26	1.57	Linear fitting	cleaned datapoints during 2021 (may-nov is removed)
16.0	0.991	14.12	1.62	random selection	-
17.0	0.987	16.90	1.59	random selection	-

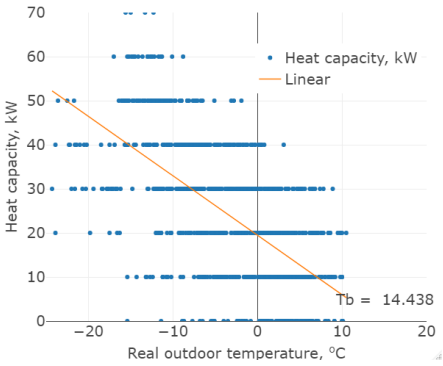


Figure 5: Base temp. calculated with heat capacity and outdoor temperature in operation time over 54%

Calculation method analysis for daily average outdoor temperature

Two calculation methods for the daily average outdoor temperature was analysed for HDD normalization. The monthly degree day analysis between both methods in Figure 6 show that the correlation in between datapoint selection method is significant. However, calculating CV(RMSE) and NMBE between daily HDD normalisation and TRY AHU heating consumption for two methods, can see that second method is more accurate (Table 3).

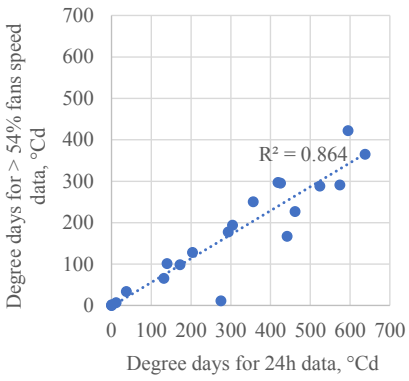


Figure 6: Correlation between two method monthly degree days

Table 3: Uncertainty calculations for data selection methods for temperature averaging

Method	CV(RMSE)	NMBE
24h data	3.95	0.46
> 54% data	2.05	0.21

Normalization methods comparison

The result of analysis is shown in the following Figures 7-9 daily, weekly and monthly. On a linear regression graphs, the horizontal axis is the AHU heat energy calculated with hourly TRY outdoor climate. On the vertical axis is the heat output/heating energy normalized with MT (upper/left) and normalized with HDD method (lower/right).

Daily and weekly analysis (Figure 7 and Figure 8) shows, that MT method will normalize just a little more accurate than HDD method. However, in monthly normalization there is no difference. Hence, the HDD normalization is more reasonable, as it does not need parameters detection.

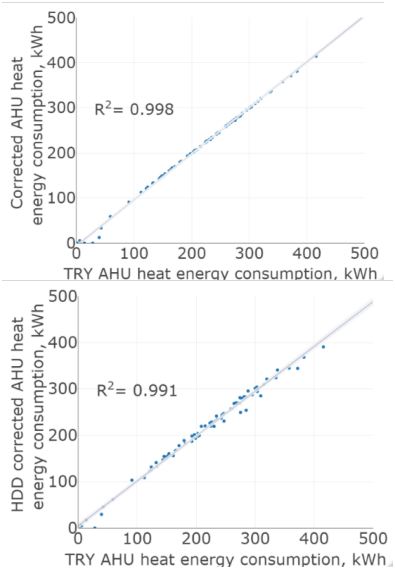


Figure 7: Comparison of daily TRY, MT (left) and HDD normalized (right) energy consumption

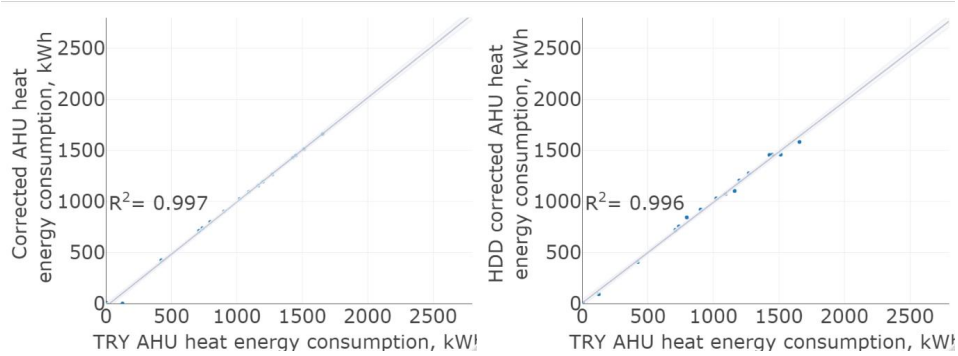


Figure 8: Comparison of weekly TRY, MT (a) and HDD normalized (b) energy consumption

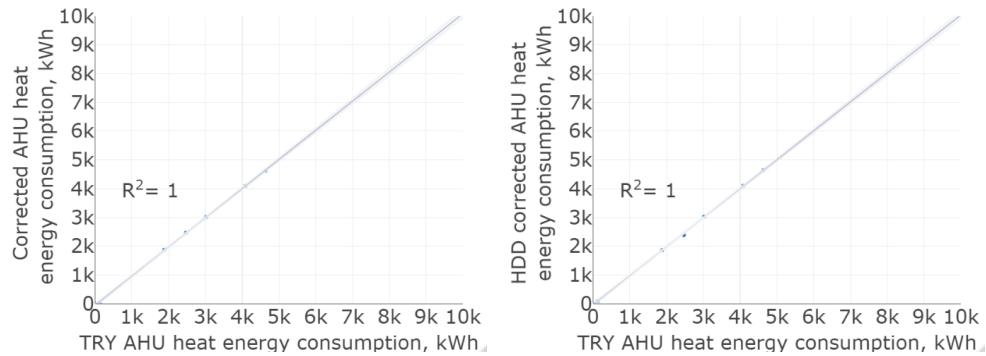


Figure 9: Comparison of monthly TRY, MT (a) and HDD normalized (b) energy consumption

Metered heat consumption normalization

Finally, the actual metered AHU heating energy consumption was normalized with HDD method from Aug-2020 to April-2022. The normalization was done with two data selection:

1) All 24h outdoor temperature was included (except may-nov);
2) Outdoor temperature during fans minimum speed 54%;

The difference between two method is not big, but varies more from Nov-2020 to Mar 2021 (Figure 10). However, another thing to notice in Figure 10 is that the energy consumption in 2021-2022 winter is low, even though the degree days are similar or even more than 2020-2021 winter. For example, the Nov-20 and Nov-21 energy consumptions are totally different, but degree days are similar. Looking to BMS of the AHU we can see, that the air flow has changed and therefore the heat recovery efficiency was improved and heating demand is lower.

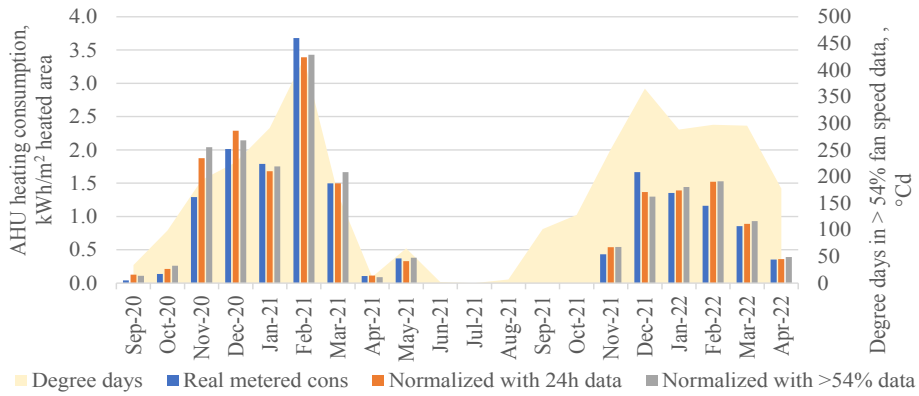


Figure 10: Comparison of monthly metered and HDD normalized energy consumption

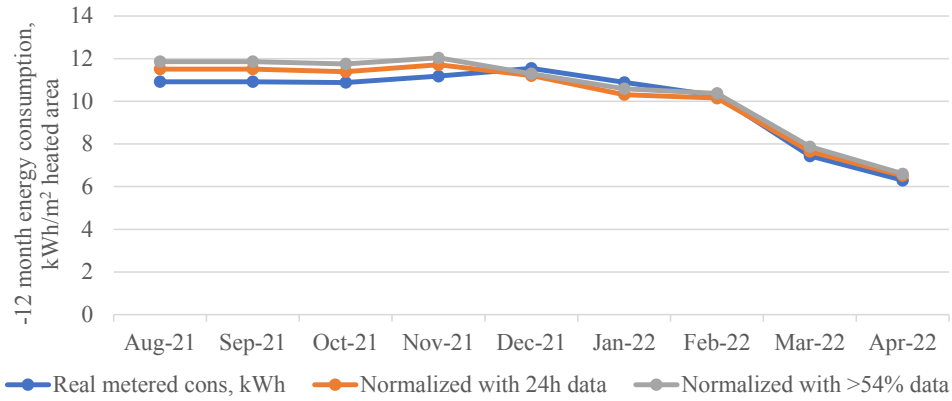


Figure 11: Yearly energy consumption calculated from 12 previous months

Figure 11 will show the 12 previous months (one year) total energy consumption calculated each month. There can see, that the real metered energy consumption will vary compared to normalized consumption. Furthermore, with this graph we can find out that from Nov-2021 something changed and should be investigated. In this case, on Nov-2021 the AHU air flow was changed.

Conclusion

This study compares two AHU heat coil heating consumption weather normalization calculation methods for the of one school building AHU with rotor heat exchanger. The mean temperature method is slightly more accurate than heating degree day method. However, there should consider that the MT method will need more data as heat recovery efficiency and AHU supply and extract temperature. Therefore, the HDD method will be more reasonable to use together with correct base temperature calculation in monthly normalization.

In AHU heat coil heating consumption analysis and normalization, the operation time should be considered as it will influence the results. Furthermore, the weather normalization is essential to erase weather influence and then predict some faults and setpoints changes.

However, it should be considered, that these analyses do not include possible frost protection and defrosting energy use. Therefore, future studies should include to the analysis some frost sensitive heat exchangers as for example, cross-flow plate heat exchanger. Furthermore, future studies should be extended to building level as in actual case, most buildings have data only for whole ventilation heating.

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PUBLICATION IV

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Data-driven baseline generation for post-retrofit energy saving assessment, a comparison of statistical and machine learning methods

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ABSTRACT

The renovation wave aims to improve energy performance of the existing building stock, encouraging development of methods for predicting post-retrofit energy use and quantifying savings. Therefore, establishing an energy use baseline is crucial for computing changes and savings. Data-driven techniques vary in effectiveness for this purpose. Selecting a suitable data-driven method for post-retrofit energy use modelling requires choosing between several approaches. This study compares two methods of establishing a baseline for post-retrofit evaluation, focusing on predicting heating and electricity energy use. One method utilizes monthly degree-day normalisation and baseline derivation, and the other employs machine learning techniques, including clustering to address seasonal variations and non-linear regression models like random forest and neural network. The comparison was based on CVRMSE, obtained by applying the methods to eight datasets. These individual datasets included metered and simulated data for heating and electricity energy use in two large non-residential buildings. An upper error margin of CVRMSE 25 % for annual energy use, as set in ASHRAE Guidelines, was not reached. The actual uncertainty during validation with simulated data ranged from 4.5 to 10.4 % for heating and electricity models using the degree-day method, and from 1.4 to 7.5 % for machine learning models. When applied to metered data, the degree-day method showed an uncertainty of 8.4–19.3 %, while machine learning models had an uncertainty of 6.11–17.5 %. Additionally, monthly percentage error analysis confirmed a considerably better performance of the machine learning models. This study contributes to the assessment of renovation impact and operational energy savings by offering additional perspectives on selecting energy use modelling methods, which are also applicable in the context of Minimum Energy Performance Standards.

Abbreviations

Degree-days – the sum of temperature difference over time. The temperature difference is between a reference and outdoor temperature, where the reference temperature is base temperature (balance point temperature) that is the outdoor temperature at

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which the heating (or the cooling) systems do not need to run in order to maintain comfort conditions [1].

1. Introduction

1.1. The call for energy use prediction methods

Buildings account for 36 % of greenhouse-gas emissions in the European Union (EU) and to reduce the amount of carbon emissions, 70 % of the building stock must be renovated. Under the Green Deal, the minimum EU-level efficiency standard obligates prioritizing the renovation of the worst-energy-performing buildings. In this respect, 15 % of such buildings in the EU have been assigned the lowest energy performance certificate (EPC), class G (inefficient). Therefore, they must be upgraded to at least class F by the year 2027 and class E by 2030 [2].

Some regulations, such as Minimum Energy Performance Standards (MEPS), are expected to enforce building renovations. MEPS will require each building to meet the minimum level of energy performance before sale or lease change, obligating efficiency upgrades to achieve the required energy performance level. Such regulations will help achieve energy efficiency targets [3].

In order to assess progress, the impact of the upgrades and renovations must be quantified and evaluated using standard methods. To adequately assess the changes in energy use due to building renovation, an energy use baseline must be established. This can be done by calculating weather-normalised energy use or developing a model for pre-retrofit energy use in case of retrofit impact assessment, using e.g., linear regression, change-point linear, variable-base degree-day or Machine Learning models. The resulting energy baseline allows for the assessment of changes in energy use and the evaluation of energy savings in the post-retrofit period (Fig. 1).

Post-retrofit energy use changes and savings are calculated according to the workflow outlined in Table 1, which shows several methods for modelling energy use and establishing an energy baseline. One method is the calibrated simulation approach using hourly building energy simulation software (Table 1, Phase 2). This method requires significant time to set up and calibrate the building energy model in the software. The initial calibration relies on certain threshold values, conditions, and limitations, such as standardised occupancy schedules or outdoor design temperature. Further model calibration may require extensive data input regarding building operating conditions, which can be obtained through monitoring.

Alternatively, using the empirical or black-box approach (Table 1, Phase 2) with historical energy use data that captures full building dynamics, requires less time to prepare, considering the scope of complex, commercial buildings, and allows for an initial evaluation of changes in energy use within the first year after renovation. While historic data cannot predict future building operating conditions, as they are not likely to be correlated with external factors, the energy use baseline does not account for changes in building utilisation. Therefore, the comparison is done to evaluate the changes resulting from the renovation of the building and technical systems. The assessment includes adjusting energy use to new weather conditions while keeping building utilisation and operation consistent, essentially comparing energy use under identical operating conditions.

Grey-box modelling (Table 1, Phase 2), particularly in the context of building energy use, is a hybrid approach that combines physical and statistical modelling. In this method, the model is initially formulated with physical relationships, which describe the dynamics of the system, and the final model structure is established using statistical methods and estimations techniques [6]. While this approach is effective for tasks such as control optimization and heat dynamics analysis, it may not always be the best option for predicting energy use in complex and dynamic environments. Li et al. [7] discuss that although brey-box models excel in optimization and parameter estimation, they encounter difficulties with straightforward prediction tasks. In such cases, black-box model or detailed simulations, with their focus on prediction, might offer more reliable outcomes.

As buildings become more advanced and incorporate smart energy meters, obtaining the necessary data becomes easier, making the application of data-driven methods more feasible and attractive. In additions, today's computational methods are becoming easier to implement on personal computers. Currently, there is a range of statistical and machine learning methods available that utilise varying levels of time resolution (granularity) in the data – from monthly energy bills [8] down to 15-min intervals [9]. The traditional

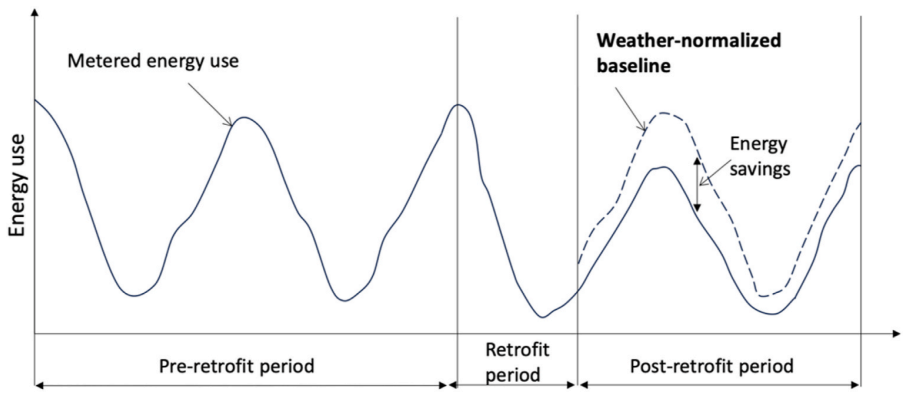


Fig. 1. Energy savings calculation description.

Table 1
The energy saving calculation phases.

Phase	Description of the phase action
1 Data gathering and pre-processing	Gathering energy use data under normal operation of the building from pre-retrofit period (Fig. 1). The data may vary in granularity, ranging from utility bills to very frequent intervals such as every 15 min. The data may require pre-processing to address issues like missing values or outliers.
2 Selecting energy use modelling method	Selecting the method: - Empirical or black-box approach (statistical or machine learning). - calibrated simulation approach. - grey-box approach
3 Developing a baseline model or training a model	Training a model for energy use prediction (machine learning) or developing a baseline model (statistical). The independent (e.g., outdoor temperature, degree-days) and dependent (energy use data from pre-retrofit period) variables are used for modelling or training.
4 Calibrating and validating the model	Calibrating the model and assessing the model's quality with statistical indicators. Most relevant statistical indicators suggested in ASHRAE Handbook Chapter 19 page 35 [4] are NMBE[a] and CV(RMSE)[b]
5 Predicting energy use or establishing a baseline	Predicting energy use of the post-retrofit period: either with the trained model or by calculating the baseline of the energy use and adjusting it to the post-retrofit period or using the independent variables from the post-retrofit period in the pre-retrofit model [5].
6 Calculating energy savings	Calculating the energy savings by subtracting the actual post-retrofit period energy use from adjusted baseline period energy use (or from the energy use predicted according to model trained with pre-retrofit data).

[a] Normalised mean bias error (equation (6) in Methods section).
[b] Coefficient of variance of the root mean square error (equation (8) in Methods section).

steady-state method like the degree-days (DD) method is still often used because of its quick computation and lack of data. However, there are more accurate methods like linear, change-point linear models recommended by ASHRAE in the Handbook Chapter 19 page 28 [4] as used also in the ASHRAE Inverse Modeling Toolkit [5].

1.2. Data-driven solutions

1.2.1. Overview of the Great Energy Predictor competitions

Prediction as a means of post-retrofit energy use modelling has been a focus for some time, with The ASHRAE Great Energy Predictor competitions playing a significant role in advancing these predictive models. These competitions, starting with the Great Energy Predictor Shootout I and II, have been pivotal in evaluating and improving the accuracy and effectiveness of energy use prediction methods.

The first Great Energy Predictor Shootout (GEP), held in 1993, was hosted Jeff Haberl and Jan Kreider. The competition provided a four-month-long training dataset for a single institutional building, covering domestic water and hot water energy use, total electricity use, and detailed weather data. The task was to assemble statistical models to predict energy use for two following months of the dataset and another model to predict time-independent solar irradiance. Top submissions used such techniques as Bayesian non-linear modelling [10], artificial neural networks (ANNs) [11,12], ensemble of neural networks [13], and piecewise linear regression [14] were used [15,16].

The second GEP Shootout, held in 1994 by Haberl and Sabaratnam Thamilseran, focused on evaluating empirical and inverse regression models for modelling hourly whole-building energy baselines [17]. This competition used pre- and post-retrofit data from two buildings, with models evaluated on their ability to predict previously unseen data, that was withheld. The results showed that cleverly assembled statistical models could be as accurate as some neural network models [15,16,18–20],particularly in predicting energy savings post-retrofit [21].

1.2.1.1. The Great Energy Predictor III competition. The most recent, third, GEP competition took place in 2019 and aimed to benchmark various machine learning models for building energy use predictions. This web-based competitions, hosted on the data science platform Kaggle [22], attracted significant attention, with final submission number reaching almost 40 000. The competitions emphasized the ability of models to generalize across different buildings based on metadata, using a dataset that included two years of hourly readings from 2380 m across 1448 buildings from more than 15 locations.

In order to address the unique challenge of developing models that could generalize across buildings of varying sizes and energy use, participants frequently combined historical meter data (including electricity energy, domestic water energy, hot water energy, and steam), weather data (air temperature, humidity, wind speed, direction, and cloud coverage), and building metadata (gross area, number of floors, building use type, system type). The most successful models also incorporated extensive preprocessing steps and feature engineering, with ensemble methods, particularly Gradient Boosting Machines (GBMs) like LightGBM [23], being dominant. These tree-based models were often combined with other algorithms, such as such as Cat-Boost [24] and neural networks, to optimize performance [25].

1.2.2. Peer solutions

Parallel to the ASHRAE Great Energy Predictor competitions, several studies have explored various methodologies for predicting energy use in buildings. For example, Dong et al. [8] used linear regression to predict energy use for 6 buildings based on two years of electricity data from utility bills and outdoor air dry-bulb temperature in Singapore. Shin et al. [26] investigated metered cooling energy use in Texas using a three-parameter cooling (VBDD for cooling) regression model, comparing enthalpy-based and temperature-based cooling degree-day methods. Manfred et al. [27] applied the Time of the Week and Temperature (TOWT) modelling

approach to predict electricity use. The steps included identifying 'occupied' and 'unoccupied' hours using hourly data and incorporating variable-base degree-days regression, complied with ASHRAE Guideline 14:2023 [28].

Machine learning algorithms have also been extensively applied. For instance, Lumbreras et al. [29] demonstrated the use of ANNs and Analysis of Variance (ANOVA) for preprocessing the data and generating trends, while Azadeh et al. [30] documented ANN's effectiveness in handling non-linearities and diverse inputs. Similarly, Liu et al. [31] noted that Linear Regression and Support Vector Machines have shown their pattern recognition capabilities, with ANNs being noted for their ability to train on extensive historical data without overfitting. Additionally, Random Forest and Gaussian Process Regression emerged as valuable tools when limited training data is available. Additionally, Anand et al. [32] used metered total electricity data and occupancy detection for energy use modelling with machine learning algorithms for institutional buildings. They identified ANNs as the most effective among several methods. Gunay et al. [33] compared inverse modelling techniques, including change point models, regression trees, and ANNs, using hourly heating and cooling load data from 35 office buildings.

1.2.3. Common points, trends, inputs

Both the ASHRAE Great Energy Predictor competitions and peer solutions highlight several common trends and practices in building energy use prediction with machine learning techniques. Feature engineering, data preprocessing, and the use of ensemble learning methods are common across the field. Ensemble methods, GBMs, and ANNs have consistently emerged as top-performing models, underlining the importance of combining predictions from multiple models to enhance accuracy.

The most common inputs across these methodologies include historical meter data and weather data, with building metadata being incorporated to enhance model's generalization capability. These inputs are essential for model training and tuning, with data preprocessing and feature engineering playing critical roles in improving prediction accuracy. Therefore, some approaches with machine learning techniques cannot be streamlined and require manual data exploration [25].

In contrast, the degree-days method is widely used for statistical and monthly based calculations. This method primarily relies on hourly or daily average outdoor air dry-bulb temperature and a base temperature, which is usually fixed in national methodologies. However, Lindelöf [34] researched the estimation of the base temperature and suggested that the arbitrary base temperature should be validated by plotting "the energy consumption against the heating degree-days calculated with that base temperature and verifying that the dependency is linear and goes through the origin (after controlling for any base load)." Previous studies [35–37] have explored the dependency of parameters and the uncertainties in calculating energy use with different base temperatures.

Despite these advances, there remains a further research opportunity in building energy prediction related to the seasonal differentiation of energy savings, as was concluded by Miller et al. [25]. Although acknowledged as a potential area for future competitions, seasonal differentiations were not the focus of GEPIII. This point is crucial as energy use patterns vary significantly between seasons, affecting the accuracy of predictions and the evaluation of retrofit impacts.

1.2.4. Error evaluation and assessment methodology

Accurate prediction is critical for ensuring the reliability of energy use baselines, particularly for renovation impact evaluation. The mentioned studies documented the achieved accuracy. For instance, Dong et al. [8] reported an annual percentage error below 5 % for most buildings, while Shin et al. [26] found monthly percentage errors ranging from −0.5 % to 13.3 % with the enthalpy-based method and daily CV(RMSE) from 9.3 % to 20.3 %, depending on the weekday. Manfred et al. [27] achieved monthly CV(RMSE) between 20.0 % and 28.5 % across four monitoring periods, noting that the post-COVID-19 period was poorly explained by the models due to changes in energy use. Machine learning approaches have also shown varying accuracy. Anand et al. [32] found that the ANN achieved a CV(RMSE) of 24.4 % during validation, outperforming a Random Forest model (over 30 %). Gunay et al. [33] reported CV(RMSE)

Table 2
Models' uncertainty in peer studies.

Author	Method	Data	Results			
			PE, %	Annual CV(RMSE) in training period (month)	Annual CV(RMSE) of prediction (day)	Annual CV(RMSE) or MAE of prediction (hour)
Dong et al. [8]	Multiple regression model with outdoor temperature	monthly electricity energy use	<5 % (annual)	2.78 to 3.8	–	
Shin et al. [26]	3PC regression model - enthalpy-based	daily cooling energy use	−0.5 %–13.3 % (month)	–	9.9 % and 20.4 %	
Manfred et al. [27]	TOWT	hourly electricity energy use	–	–	–	CV(RMSE) 20.0–28.5 %
Anand et al. [32]	ML algorithms (electricity and occupancy)	hourly electricity energy use	–	–	–	CV(RMSE) MAE ANN-DN 24.4 % 23.6 ANN-FF 27.9 % 26.4 RF 35.3 % 37.6
Gunay et al. [33]	change point models (CP), regression trees (RT), and ANN	hourly heating, cooling energy use	–	–	–	CV(RMSE) (training) CP 4–20 % RT 4–18 % ANN 3–16 %

ranges from 4 % to 20 % for change point models, 4 %–18 % for Regression Trees, and 3 %–16 % for ANNs. These results from the mentioned studies are summarized in Table 2, which covers the methods, data used, and accuracy achieved in these studies.

In contrast, the Great Energy Predictor III competition used the Root Mean Squared Logarithmic Error (RMSLE) as the evaluation metric. Unlike regular RMSE, RMSLE includes an additional step: taking the natural logarithm of both actual and predicted values. This transformation ensures that the results are not skewed by the naturally larger energy use of bigger consumers, thereby preventing the prediction error from being disproportionately affected by the scale of the values [38]. This makes RMSLE particularly suitable for comparing models that generalize across different buildings. However, the results must be compared with caution, due to the different scales and units of error between peer solutions and GEPIII. The winning teams, short approach descriptions as well as score from GEPIII are covered in Table 3.

ASHRAE Guideline [28] offers detailed instructions for energy prediction and savings calculation, while EVO IPMVP [40] is a broader protocol for these processes. This study focuses mainly on whole-building approaches as covered in both the guideline and the protocol. Fu et al. [41] noted, that "one of the many values of the whole-building approach is its ability to quickly assess the building energy use pattern without detailed information about its system configurations, occupancy schedule, space type, etc., which reduces the cost of this activity." Following the ASHRAE Handbook – Fundamentals [4], this study uses data obtained under normal operation, first composing a simulation model to generate energy use data for the validation.

In his doctoral thesis [42], Kissock mentions that daily energy use is correlated with the variation in mean daily temperature, with R^2 statistics for temperature-based simple linear regression models of energy use ranging between 59 % and 88 %. The remaining variability may arise from changes in internal loads or operating procedures, or from the variation of other environmental variables besides temperature, which also impact cooling and heating energy use. This highlights the importance of selecting an appropriate timeframe for energy use assessment.

1.3. Purpose and novelty

Data-driven techniques have shown varying effectiveness in predicting building energy use. When selecting a method for post-renovation energy savings calculations, choosing between a conventional degree-day (DD) method and a machine learning (ML) approach is an important question, under the condition that hourly historical energy data is available. If hourly energy data is not available, the robust DD method can operate with monthly energy bill data. Therefore, it is a question how much better accuracy can be achieved with ML method which application needs more data and effort. In this paper both methods are applied to cooling energy, included in total electricity use, and heating energy, to determine which is more suitable for each application. In principle such comparison of monthly DD method with hourly ML method is not fair. However, it is justified because both methods are practical options for establishing a post-retrofit energy use baseline, with offering faster alternatives to the calibrated simulation approach by utilising historical data. While ML method will need hourly data, it is still much faster alternative to a whole building energy simulation model that needs detailed input data, modelling and calibration effort to be applied. Thus, we aim to benchmark the newer ML approach against the degree-day method, a robust and well-established benchmark in the industry.

The study focuses on predicting energy use for the entire year with monthly time resolution, allowing for comprehensive renovation impact assessments. Yearly evaluations cover seasonal and daylight variations as well as changes in occupancy patterns, aligning with efficiency standards and assessing long-term impacts. Meanwhile, monthly analyses provide more detailed insights that can help identify trends or issues not visible in yearly data, enabling timely response to unexpected changes. While the ML method requires hourly data, the monthly scale of evaluation is convenient and relevant to building managers, as month-to-month comparisons are easy to follow.

The first approach in our comparison is the statistical DD method, normalisation with degree-days, while the second utilizes ML techniques, including clustering and regression modelling. By clustering independent variables, distinct energy use conditions and periods are formed, addressing the significant research question – seasonal differentiations, addressed by Miller et al. [25]. This approach captures seasonal variations, allowing regression models for each energy use cluster to be tailored to specific conditions, thereby capturing nuances that a single model might miss.

These methods can be applied in buildings where energy renovation or improvement measures have already been implemented, and where pre-retrofit energy use is known from energy bills or metered with hourly resolution. The findings can offer insights for assessing operational energy savings and help determine which approach is more suitable for implementation in the context of Minimum Energy Performance Standards (MEPS).

Table 3
Top teams, approaches and scores in the Great Energy Predictor III competition.

Place	Team	Approach	Score over one year data (RMSLE)
1	Matthew Motoki, Isamu Yamashita	Group-based ensembles using LightGBM [23], Cat-Boost [24], MLP	1.231
2	Rohan Rao, Anton Isakin, Yangguang Zang, Oleg Knaub	Intensive pre-processing and a huge XGBoost [39], LightGBM [23], Cat-Boost [24] and feed-forward Neural Network ensemble	1.232
3	Xavier Capdepon	Cat-Boost [24] and LightGBM [23] with weighted post-processing	1.234
4	Jun Yang	XGBoost [39] and LightGBM [23]	1.235
5	Tatsuya Sano, Minoru Tomioka, Yuta Kobayashi	LightGBM [23] ensemble with post-processing weighting	1.237

2. Materials and method

The study involves the use of hourly heating and electricity data obtained from metered data sourced from reference buildings (described in Section 3.2). The investigation focuses on predicting the baseline of building energy use, which serves as the reference energy use for post-retrofit savings assessment. The following two approaches (detailed in Section 3.1) are used for the prediction:

1) Fixed degree-day based monthly (DD) method - an empirical and engineering-based technique that uses degree-days for predicting monthly energy use.
2) Machine learning method - a three-phase approach utilising both unsupervised and supervised Machine Learning (ML) for hourly data, developing models for heating and electricity energy use.

The prediction methods were first validated in predefined conditions - using data from simulation models (in detail in Section 3.4). Subsequently, the application of the methods was analysed with actual metered data from 2017 to 2022. Both processes involve comparing model predictions with simulated or actual data and calculating the uncertainty of the prediction, following ASHRAE Guideline 14–2023 [28]. Therefore, the model prediction workflow and uncertainty analysis are identical for validation and application analysis (described in more detail more in Sections 3.4 and 3.5). The input for the prediction models is described in Section 3.3.

2.1. Description of the energy use prediction methods

2.1.1. Degree-day based energy use prediction method

The fixed degree-day based (DD) energy use prediction approach involves data analysing and monthly weather normalisation to generate a baseline prediction with monthly granularity. Monthly degree-days are calculated with hourly average outdoor temperature in the billing period (when the energy was used), and base temperature. The base temperature was fixed, because this method is not very sensitive to this variable (Fig. 2). Base temperatures used in this study found to be most suitable for the generalization.

This process is based on the monthly heating and cooling degree-days and total energy use from main meters for those specific months. The overarching principle of the method is outlined in Fig. 3 and can be summarized as follows: (1) Identification of the weather-dependent component of the energy use, (2) Normalisation of this component to base year weather conditions using a monthly weather normalisation coefficient (c_DD calculation explained in Fig. 4), to establish the baseline model, and (3) Utilisation of the weather normalisation in reverse to project baseline and therefore, predict energy use under specific year weather conditions. This was used to compare the predictions with actual metered data. The input to the monthly-based model was:

- Degree-days (outdoor temperature and fixed base temperature)
  - o For cooling (electricity energy use), with base temperature 10 °C (50 °F)
  - o For heating, with base temperature 15 °C (59 °F)
- Thresholds for the normalisation coefficients calculation:
  - o c_DD = 1, if CDDs <60
  - o c_DD = 1, if HDDs <50
- Days in month
- Metered monthly energy use (aggregated simulation output or metered data) (MWh)

2.1.2. Machine learning method: random forest and neural network models on hourly basis

The process of the ML method was carried out in three phases, using both unsupervised and supervised learning techniques: (1) data pre-processing, (2) clustering, and (3) scenario-specific regression modelling (Fig. 5). This approach analysed hourly data to predict long-term energy use baselines, with each hourly prediction based on the independent variables at those specific times contributing to the overall baseline. These hourly predictions were then aggregated to monthly values, which were compared against the results from the DD-based energy use prediction method.

Segmented modelling through clustering and regression offers significant advantages. This approach captures variations within different groups of energy use that a single model might miss. Each cluster is modelled with a regression tailored to its specific

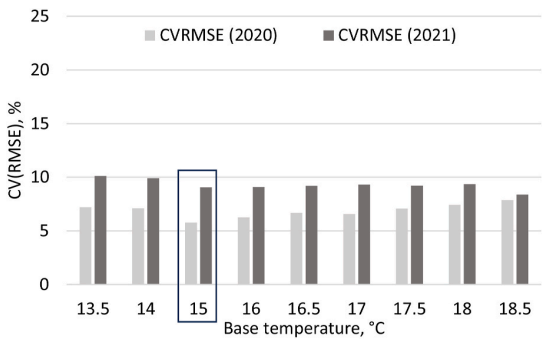


Fig. 2. The uncertainty of DD model predicting the heating energy use of RB2 (with simulation model data) with different base temperatures in 2020 and 2021.

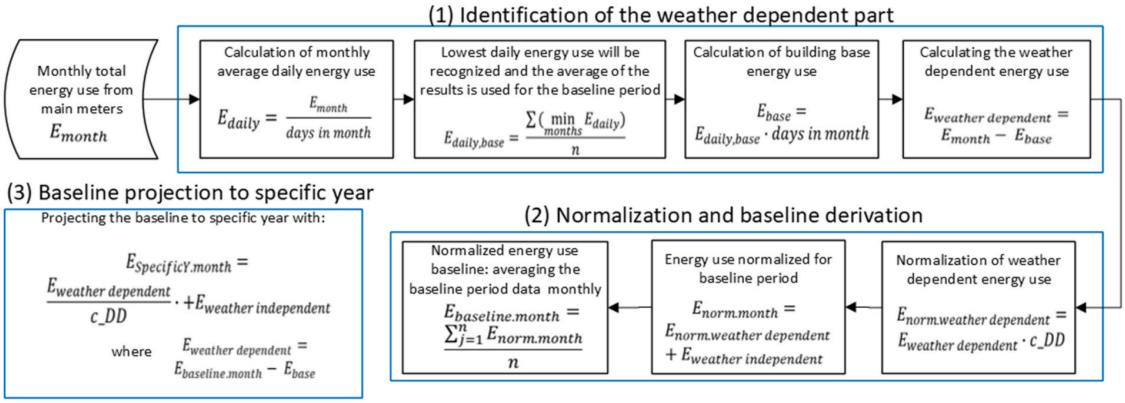


Fig. 3. The flowchart of degree-day based method (n is the number of months used in the calculation phase).

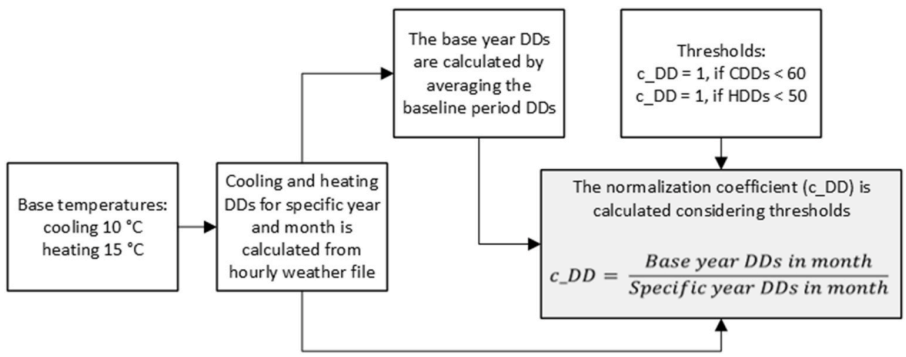


Fig. 4. Degree-days calculation method.

characteristics, simplifying relationships between features and the target variable. This combined method effectively handles variation in the data and can enhance predictive accuracy.

2.1.2.1. Data pre-processing. The first phase involved pre-processing the raw data and selecting key features, based on domain-specific knowledge and various combinations. The raw data included:

- Date and time data,
- Weather data: outdoor air temperature [°C], relative humidity [%], direct normal and diffuse horizontal solar irradiance [W/m^2],
- Hourly energy use data normalised to heated floor area [W/m^2].

A pre-processing algorithm expanded the raw data into a broader set of features (Table 4). Features included occupancy-related variables (date, time), and weather-related variables influencing energy use. Feature-engineered variables such as the 'monthly sunlit ratio', which quantified sunlit hours each month, and projections of direct normal irradiance (DNI) on vertical planes, were used to enhance model accuracy. For the heating energy use model, the Exponential Weighted Average (EWMA) of outdoor air temperature and solar irradiance were used, while the electricity energy use baseline model utilised the specific enthalpy of air to indicate latent heat removal during air conditioning.

The feature sets for clustering and regression were distinct, each selected for its impact on model outcomes. Clustering included

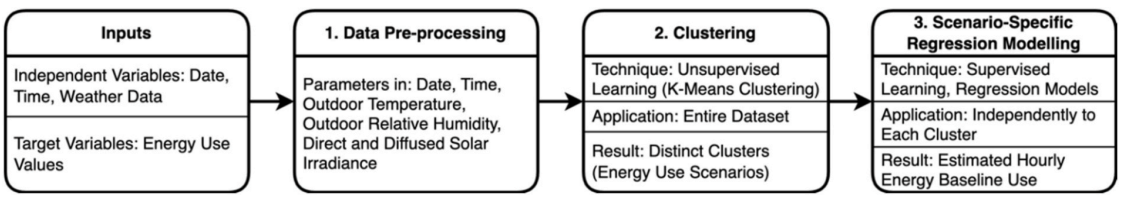


Fig. 5. Outline of the hybrid machine learning method.

Table 4
Included model features depending on the method phase and target.

Target baseline prediction:	Heating energy		Electricity energy		Value ranges
Features:	Clustering	Regression model	Clustering	Regression modeling	
Weekday or the weekend	x		x		0/1
Hour sine	x		x		[-1.0, 1.0]
Hour cosine	x		x		[-1.0, 1.0]
Hour of the day		x		x	[0, 23]
Solar hour angle		x		x	[-180.0, 165.0]
Monthly sunlit ratio	x	x	x	x	[0.16, 0.84]
Solar altitude angle	x	x	x	x	[-41.4, 41.4]
Outdoor air temperature		x		x	[-17.3, 33.7]
Outdoor air temperature, EWMA*, window size of 6 h	x		x		[-16.7, 31.9]
Direct solar irradiance projection on a vertical plane		x		x	[0, 920.0]
Diffused solar irradiance projection on a vertical plane		x		x	[0, 250.3]
Summarized projection of solar irradiance, EWMA*, window size of 2 h	x		x		[0.0, 927.1]
Relative humidity of outdoor air			x		[19, 100]
Specific enthalpy of air			x	x	[-15.7, 68.7]
*EWMA – exponential weighted average					

features that significantly affected the identification of energy use scenarios, while regression prioritized accuracy improving features capturing daily energy dynamics. For instance, the use of 'Hour of the day' was used in regression models to provide a linear time representation, while sine and cosine transformations offered more insight for the clustering algorithm. Although sine and cosine transformations can be used in regression models, as well, their exclusion can simplify the model and potentially improve accuracy if the direct time representation is sufficient for the prediction task.

The features for the regression models were added using a manual forward selection approach. This process was not automated, and no conventional statistical tests were conducted. Features were added one by one until the performance showed no significant improvement, using a threshold of 0.05 for the coefficient of determination (R^2) to determine the significance of the improvement.

Time values were represented via two components – sine and cosine – to reflect the cyclic nature of time and improve performance in distance-based algorithms. This transformation was done according to Equation (1), where h represented the hour value [43].

$$\sin\left(\frac{2\pi h}{24}\right), \cos\left(\frac{2\pi h}{24}\right) \tag{1}$$

An additional step included scaling features to ensure that features with larger value range would not disproportionally influence the models' results. The features were scaled using Z-score scaler, which standardizes features by removing the mean from each variable and scaling it to unit variance (2).

$$Z = \frac{(x - \mu)}{\sigma} \tag{2}$$

2.1.2.2. Clustering. In the second phase, clustering was used to enhance accuracy of energy use baseline predictions, by capturing different conditions and periods in the data. Clustering is a general term that covers several types of techniques, commonly including representative-based, hierarchical, probabilistic, and density-based algorithms [44]. The choice of algorithm depends on the specific objective. We aimed to cluster energy use data based on temporal and climatic features to form distinct energy use scenarios under various conditions. This can be effectively achieved using the straightforward hard clustering algorithm, k-means [45]. As we only needed distinct group and not probabilities or sequential patterns, k-means was well suited for the task.

The k-means algorithm aims to minimize the errors between the points and their respective centroids, ensuring that the points are as close as possible to the centroid of the assigned cluster. This is achieved by minimizing the sum of squared Euclidean distances between the points (x_i) and their respective centroids (μ_j) across the set of all cluster centroids (C) (3) [44].

$$\sum_{i=0}^{n} \min_{\mu_j \in C} \left(\|x_i - \mu_j\|^2 \right) \tag{3}$$

The optimal number of clusters (n) was determined using the elbow method. This involves calculating the within-cluster sum of squared errors (SSE) (4), which is the sum of squared differences between each data point (x_i) and the centroids of the assigned cluster ($\mu_{c(i)}$). The point where adding more clusters did not cause a significant decrease in error [44] selected algorithmically by comparing the changes in SSE values during iterations over different number of clusters.

$$SSE = \sum_{i=0}^{n} (x_i - \mu_{c(i)})^2 \tag{4}$$

2.1.2.3. Scenario-specific regression. In the third phase, regression models were applied independently to each formed cluster or

scenario to predict hourly energy use values. The regression models were not autoregressive, meaning that each hourly prediction was made without relying on previous hour values. This approach prevents the accumulation of errors over times and ensures that each prediction is based on the current hour's conditions.

The ASHRAE Great Energy Predictor competitions have demonstrated the effectiveness of ensemble methods and neural networks in building energy use prediction. In the most recent competition, ensemble methods were utilised by top performers, highlighting their robustness and accuracy. These competitions have shown that ensemble methods can effectively handle complex datasets and improve predictive performance. Neural Networks (NNs) were effective in capturing non-linear relationships and patterns in the data.

Based on these findings, we decided to test an ensemble method – Random Forest (RF) – and a steadily proven method – NNs. RF forms an ensemble of decision trees, where each tree makes splits in the data based on the most indicative feature values, and the final prediction is based on all the trees' outputs. This method is preferred for its interpretability and resistance to overfitting. NN's, on the other hand, consist of layers of interconnected nodes that can capture complex relationships in the data through non-linear transformations. Despite RF's larger file sizes and NN's computational intensity, both models were tested for comparison reasons, as the primary focus was on baseline accuracy [45].

2.1.2.4. Model validation against overfitting. In order to test the regression models' settings (Table 5) for overfitting, the actual and predicted target values were compared using Mean Average Error (MAE) as an indicator. Firstly, the difference between the actual heating energy use values for years 2018 and 2019 were compared (year-to-year). Secondly, two regression models based on 2018 data were trained and predictions were made using 2019 independent variables. The MAE for predictions and actual 2019 target values was computed (model-to-2019), revealing smaller values and indicating that the models had not replicated training target variables, but had captured the general behaviour instead. The MAE values are shown in Table 6.

2.1.2.5. Model training. After obtaining the pre-processed features, they formed an input feature vector, representing the conditions for each logged energy use value. As it is shown in Table 4, the feature values were in different ranges. Before passing these vectors to the k-means algorithm, a scaling operation was performed, and the scaler was saved for future application step. The scaling step ensured all features were set within a similar range, minimizing the potential influence from larger scale variables on the clustering outcomes. Then, the scaled features were passed to the k-means algorithm, the second phase of the approach. The optimal number of clusters for the algorithm was automatically determined using the elbow method. Afterwards, the clusters' centroids values were obtained, and each input vector was assigned to a specific cluster. The centroid values were saved for the future application. The third phase of the approach was done repetitively for each formed cluster. During the third phase, two regression models were tested, and the aggregated results evaluated based on several performance indicators.

2.1.2.6. Model application. A validation set, formed based on data from different periods (see Results), was processed by assigning each entry individually to the nearest centroid of a cluster, determined during the cluster training phase. Following that, regression models were applied to each of these entries, depending on the assigned cluster, to predict the hourly energy use (baseline). These predictions were then aggregated into monthly totals for further analysis. Fig. 6 demonstrates the described approach detailed structure.

2.2. Case studies and method validation

Reference buildings include an office building (heated floor area 16 990 m^2) and a university building (heated floor area 10 360 m^2). The metered data was gathered from building owners. The simulation models created in IDA Indoor Climate and Energy 4.8 (IDA ICE) software [46], are calibrated and validated with ASHRAE Guideline 14–2023 [28], ensuring a computer model with 5 % NMBE and a CV(RMSE) of 15 %. Building performance simulations used 2017–2021 Estonian historical weather data, the same as in prediction models. For both simulation models, the cooling electricity was calculated with COP = 3.5. Other main parameters for the model's description were taken from and energy use calculations were done according to Estonian regulation for energy performance calculation [47].

2.2.1. Reference building 1

Reference building 1 (RB1), illustrated in Fig. 7, is actively used, 5 storey (plus basement) university building in TalTech campus with heated floor area 10 360 m^2 built in 2009. The average heating energy use in 2020–2021 (normalising to the Estonian test reference year) was 156 kWh/m^2 and electricity 117 kWh/m^2. Consequently, the operational primary energy use is 232 kWh/m^2 and the EPC label is E.

The simulation model, composed using building documentation, utilised an hourly prn file for equipment and lighting power W/m^2 only for the calibration to define actual internal gains and profiles. Model was calibrated with monthly metered energy use from 2021. The comparison of metered and simulated monthly energy use is in Fig. 8. The CV(RMSE) was 10.9 % and 23.9 %; NMBE 11.1 % and 17.5, respectively for electricity and heating energy use. Although the heating energy calibration did not achieve ASHRAE

Table 5
Models' configurations.

Model	Function	Hyperparameter	Value
Random Forest	sklearn.ensemble.RandomForestRegressor	Number of trees in the forest	100
		The maximum depth of the tree	Default
Neural Network	sklearn.neural_network.MLPRegressor	Number of hidden layers	2
		Number of neurons in each layer	30
		Maximum number of iterations	100

Table 6
MAE values for overfitting control.

cluster	year-to-year	Model-to-2019 (RF)	Model-to-2019 (NN)
0	6.7	4.1	4.1
1	9.3	4.3	4.3
2	6.0	2.7	2.6
3	6.6	3.5	3.3

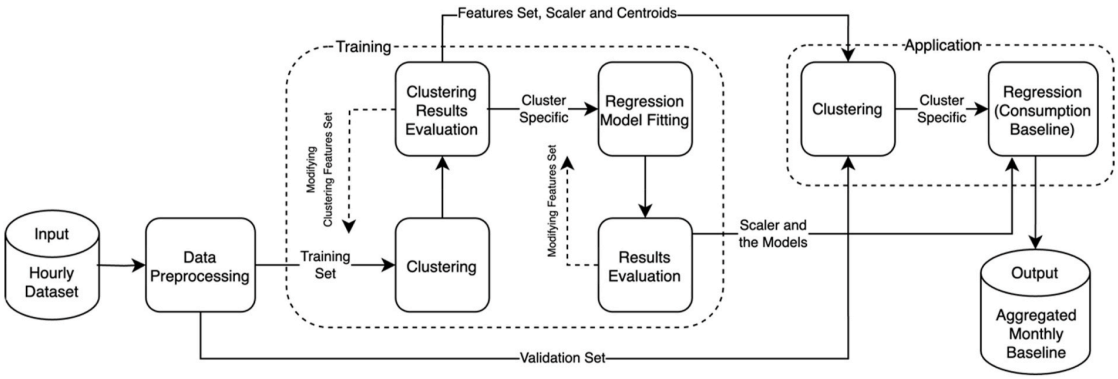


Fig. 6. Hybrid machine learning approach.

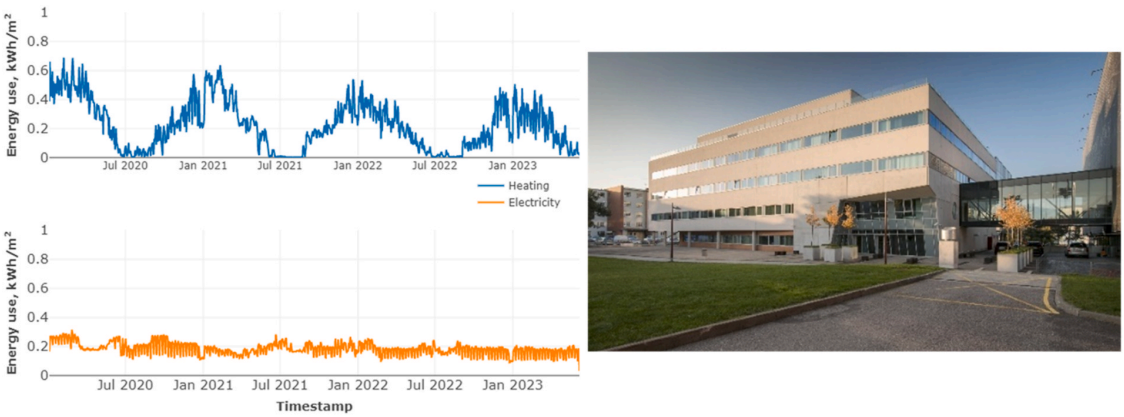


Fig. 7. Metered daily energy use (left) and the reference building 1 built in 2009 (TalTech) (right).

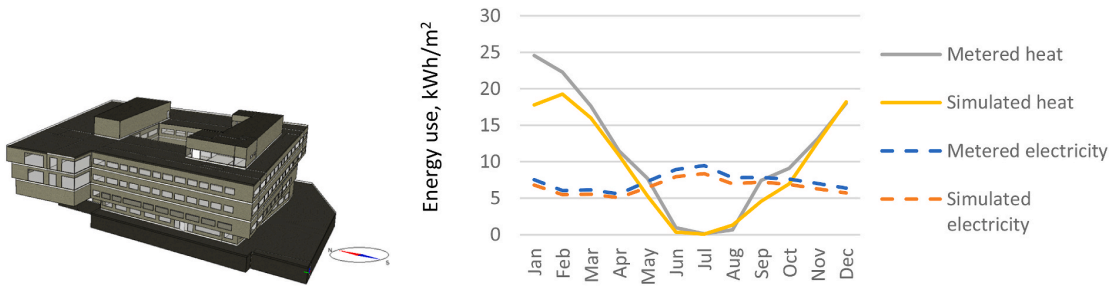


Fig. 8. Left: The reference university building in TalTech Campus. Right: Metered and simulated monthly heat and electricity energy use in 2021 for university building.

requirements, due to substantial variations in January, February and September (due to the building use in 2021 (COVID-19 period), the model considered to be appropriate for case study and method assessment. For further analysis, the simulation model's internal gains are defined as standard [47].

2.2.2. Reference building 2

The reference building 2 (RB2) (Fig. 9) is actively used and well maintained 5-story office building with heated floor area 16 990 m^2 built in 2008. Its 2020–2021 average heating energy use (normalised to Estonian test reference year) was 116 kWh/m^2 and electricity 93 kWh/m^2. Therefore, the operational primary energy use is 303 kWh/m^2 and the EPC label is F. Further details about this office building can be found in the article by Kuivjõgi et al. [48].

The calibration of the simulation model for reference building 2 involved weather and metered energy use from 2014. In terms of electricity energy use, the building model had the CV(RMSE) 10 % and the NMBE 1.7 % considering monthly calibration data. For heating energy use, the CV(RMSE) was 16 % and the NMBE -6.3 %. The comparison of metered and simulated monthly energy use is illustrated in Fig. 10. The calibration proved sufficiently successful to deem the model suitable for method assessment.

2.3. Models input and output description

In this study models produce the energy use baseline prediction for the entire year in monthly granularity. The DD method uses monthly degree-days and energy use data. The ML method uses hourly weather and energy use data to produce long-term baseline energy use prediction.

2.3.1. Selection of weather data for models

The weather dataset includes hourly outdoor air dry-bulb temperature (°C), relative humidity (%), wind speed (m/s) and direction from Tallinn-Harku weather station. Additionally, solar direct radiation to normal and diffuse radiation on horizontal surface (both in W/m^2) from the Tartu-Tõravere weather station. Notably, solar radiation data is obtained from alternative station, as the Tallinn-Harku station lacks detailed direct and diffuse solar radiation measurements. For further research with different locations, the weather data (including solar irradiation) is available in different databases all over the world (e.g., Ref. [49]). The monthly degree-days were calculated using hourly average outdoor temperature by the methodology described previously. For proper evaluation, the selected weather data spans the years 2017–2021 with different weather conditions. Fig. 11 illustrates the variations in degree days compared to the average degree days from 2017 to 2021.

2.3.2. Correlation on weather and metered data

Another input for the models was hourly (or monthly aggregated) building heating and electricity energy use. Buildings energy use is significantly impacted by outdoor conditions. The correlation between heating energy use and weather conditions emerges more in cold climates. In warm climates, usually the electricity energy use has a better correlation with weather conditions due to cooling demand. Therefore, there should be careful with the independent variables (here weather data) used in models. Otherwise, the prediction models will copy the training period data. For example, Fig. 12 and Figure A1 in appendix A illustrate that RB2's electricity energy use had little correlation with outdoor temperature and RB1 had no correlation.

The daily heating energy use of two reference buildings (blue in Fig. 12 and in Figure A1 in appendix A) correlates with outdoor temperature and direct solar radiation to normal. While the correlation with relative humidity is less evident, using it as raw data for the ML approach together with temperature will gave good results. In RB1, daily electricity energy use appears unaffected by weather conditions. However, in RB2, a correlation is evident – as outdoor temperature rises, electricity energy use increases, particularly in the 10–15 °C range.

2.3.2.1. Weather dependent energy use in degree-day method. In each case the training period of the DD method detected the weather-dependent part of total heating energy use as 80–88 %. The weather-dependent part from total electricity energy use is about 16–20 %

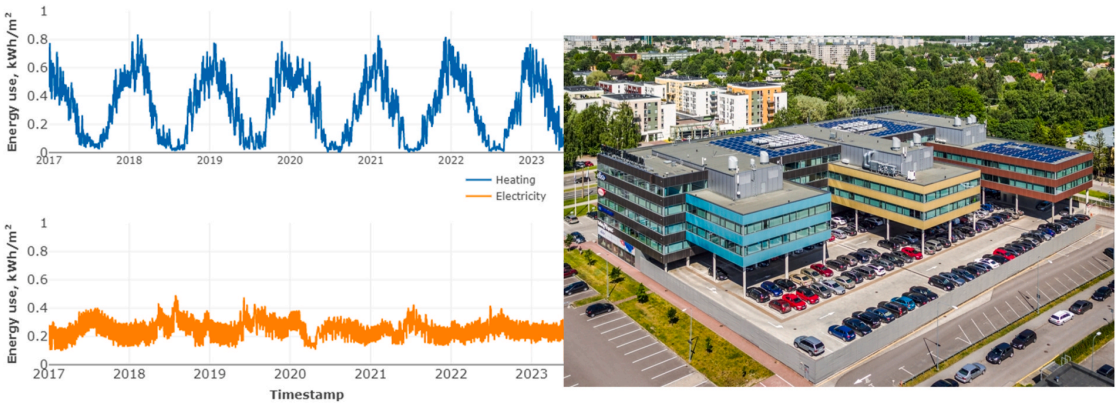


Fig. 9. Metered daily energy use (left) and the reference building 2 built in 2008 (right) (www.soprusearimaja.ee).

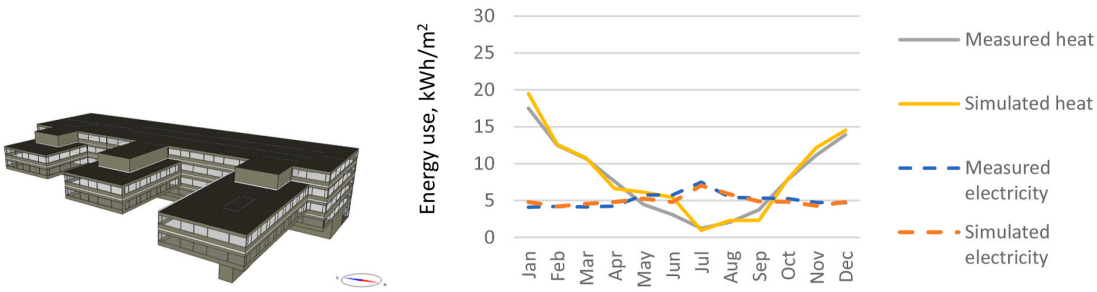


Fig. 10. Left: The reference office building in Tallinn. Right: Metered and simulated monthly heat and electricity use in 2014 for office building.

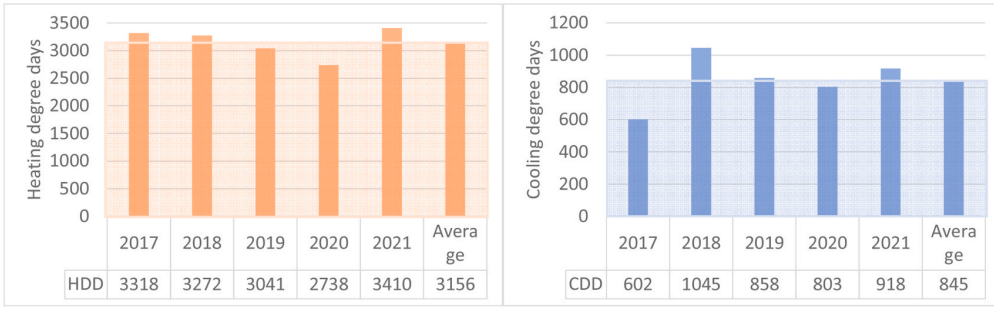


Fig. 11. The heating and cooling degree days (respectively, base temperature is 15 °C and 10 °C) compared to average degree days during period of 2017–2021. 2017 has cold winter and cold summer. In 2018 the weather is colder in the winter and warm in the summer. Weather in the summer of 2019 is average, winter is warm. Year 2020 has warm winter and cold summer. And 2021, on the contrary, cold winter and warm summer.

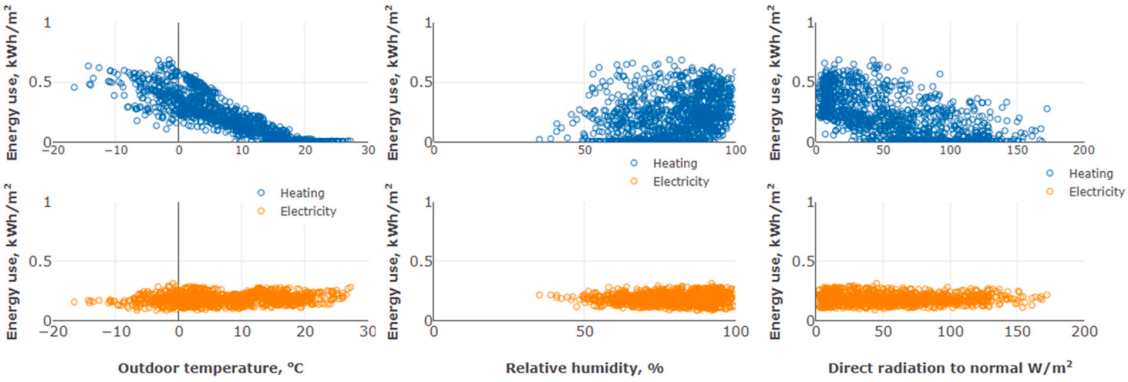


Fig. 12. RB1 metered heating (blue) and electricity (orange) daily energy use (kWh/m^2) in 2020–2023 with actual weather data in this period. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

in RB1 and 8–13 % in RB2. The base energy use and weather-dependent part detected by DD method with RB1 metered data are outlined in Fig. 13. The cooling demand data gathered from the building manager revealed that the annual metered electricity for cooling in RB1 was about 1.1 kWh/m^2 in 2021. Therefore, it is uncertain, whether the method detected the weather-dependent part incorrectly or is it some other usage that is dependent on weather, such as electricity for room lighting (the right graph on Fig. 13).

2.4. Measuring the performance of prediction models

In summary, the validation of two approaches was carried out with simulation model data. Thereupon, the actual metered energy use was used for the application analysis of the methods. The model's prediction uncertainty for validation and application analysis was calculated following ASHRAE Guideline 14–2023 [28], as described in Section 3.5.

For the validation, the energy simulations were conducted with two models (RB1 and RB2) using Tallinn weather data over the

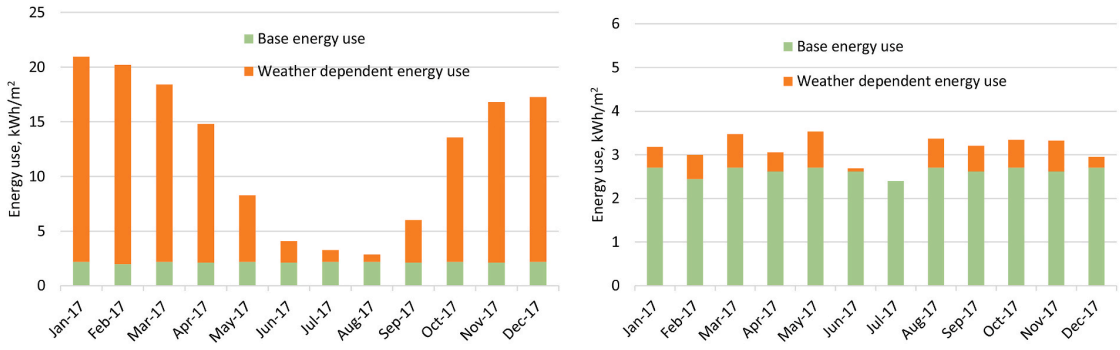


Fig. 13. Metered heating (left) and electricity (right) energy use in RB1 and detected weather dependent part by degree-day method in training period from July 2020 to July 2021.

2017–2019 period. By utilising simulation models output during the 2017–2019 period for training, the models were derived with two prediction methods. Then the energy use was predicted for 2020–2021. Subsequently, these predictions were compared against the simulation models output for the same period. The simulation models were used to collect data on energy use within predetermined boundary conditions, thereby eliminating anomalies caused by external factors like Covid and the energy crisis in 2020–2021. This focused on the performance of the predicting methods and their uncertainties.

Metered energy use data from both buildings were collected for the period 2017–2022 from RB2 and for the period 2020–2022 from RB1. This data was used to analyse the application of the prediction models in real situation. By utilising metered energy use data from RB2 during the 2017–2018 period for training, the models were derived with the prediction methods. Then the energy use was predicted for 2019. Subsequently, these predictions were compared against the metered energy use data for the same year. External factors (as COVID-19 and the energy crisis) significantly influenced the energy use in the 2020–2022 period. Therefore, in addition to pre-COVID analysis, the same procedure was done for COVID-19 period with RB1 and RB2. The training period was from July 2020 to July 2021 and prediction period was from July 2021 to July 2022. The prediction model's performance analysis is outlined in Fig. 14.

2.5. Uncertainty analysis and methods validation procedure

In accordance with ASHRAE Guideline 14 [28], this study used various metrics to measure the performance of prediction models in representing variability within simulated or metered data. The coefficient of determination (R^2 in equation (5)), normalised mean bias error (NMBE in equation (6)), Root-Mean-Square Error (RMSE in equation (7)), and Coefficient of Variation of the Root-Mean-Square

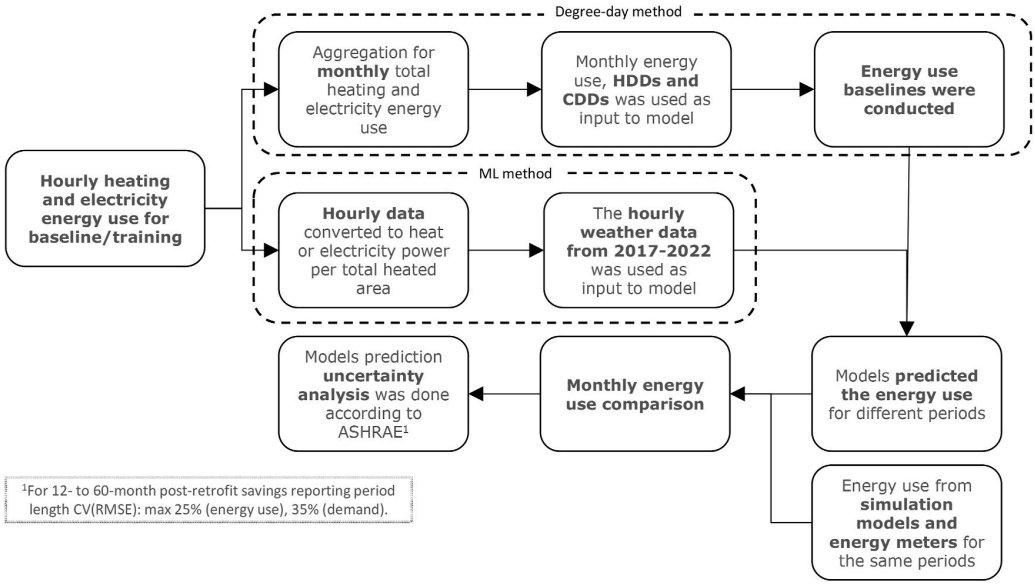


Fig. 14. Models' inputs description and uncertainty analysis of the prediction models for both, data gathered from simulation models and energy meters in 2017–2022.

Error (CV(RMSE) in equation (8)) were utilised. In these equations, Y represents monthly metered energy use (kWh/m^2), $\hat{Y}_i$ represents monthly predicted energy use at the same time (kWh/m^2), n is the number of data rows (months), $\overline{Y}$ is the mean of the metered energy use over the period (annually) (kWh/m^2), and p is the number of parameters or terms in the baseline model, considered as 0 for the prediction models in this study.

Guideline [28] defines that the baseline model should have a maximum CV(RMSE) of 25 % for energy use when computing with 12–60 months of data. While limits for R^2 are not specified, the Guideline recommends using it for identifying the best model. According to IPMVP Uncertainty Assessment [50], the R^2 test is an initial check, and models should not be solely accepted or rejected based on it. The importance of an R^2 value depends on the variance of the dependent variable, for example, a low R^2 value is less serious when the variance of the dependent variable is small, and more significant with a large variance.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{n}(Y_i - \overline{Y})^2} \tag{5}$$

$$NMBE = \frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)}{(n-p) \times \overline{Y}} \tag{6}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{n-p}} \tag{7}$$

$$CV(RMSE) = \frac{RMSE}{\overline{Y}} \times 100 \tag{8}$$

Monthly comparison used percentage error calculated with equation (9). Negative values of percentage error indicate model prediction overestimation, while positive values indicate underestimation. In savings calculation, overestimation will give higher baseline, resulting in better savings. In contrast, for future energy use prediction and EPC calculation (e.g. using weather prediction), overestimation will give us worse EPC.

$$\%error = \frac{Y_i - \hat{Y}_i}{Y_i} \bullet 100 \tag{9}$$

The mean absolute error (MAE) was calculated with equation (10).

$$MAE = \frac{\sum_{i=1}^{n}|Y_i - \hat{Y}_i|^2}{n} \tag{10}$$

The mean absolute percentage error (MAPE) was calculated with equation (11).

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_i - \hat{Y}_i}{Y_i} \bullet 100\right| \tag{11}$$

Additionally, the same evaluation metric – RMSLE (Eq. (12)) – used in the latest Great Energy Predictor competition [25] was applied to evaluate the ML approach only, as the competition had set the first benchmarks for building energy use prediction models.



	RB1 Heating 2020	RB2 Heating 2020	RB1 Electricity 2020	RB2 Electricity 2020	RB1 Heating 2021	RB2 Heating 2021	RB1 Electricity 2021	RB2 Electricity 2021
DD model	4.55%	5.75%	5.92%	4.85%	5.62%	9.04%	10.38%	8.48%
ML (Random Forest)	3.32%	3.07%	5.22%	4.25%	1.84%	2.90%	7.50%	7.48%
ML (Neural Network)	2.69%	1.74%	5.64%	4.21%	1.41%	2.92%	6.55%	6.03%

Fig. 15. Overview of the prediction models CV(RMSE) results by prediction year, energy and reference building.

$$RMSLE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\ln(1+y_i) - \ln(1+\hat{y}_i))^2} \quad (12)$$

where: n is the total number of observations, $\hat{y}_i$ is the predicted value and y_i is the corresponding actual value and $\ln(x)$ is the natural logarithm of x.

3. Results and discussion

This section outlines the results of the study and discusses the main outcomes. First, the results of the validation of the prediction models with simulation model data are outlined. The model's prediction results for the pre-COVID period are only from RB2 and for the COVID-19 period analysis is for both reference buildings. More detailed tables are provided in the Appendices.

3.1. The validation of the prediction methods

Utilising simulation models' energy use data, the validation of both prediction approaches was conducted for the years 2020 and 2021. The annual uncertainty analysis relied on the CV(RMSE) and the overall performance of different methods is shown in Fig. 15. The annual CV(RMSE) fell in the range of 1.4%–10.4 % for the prediction during the validation period. According to ASHRAE Guideline [28], the accuracy of the prediction models using simulation models' data was eligible for monthly basis baseline prediction for savings calculation. However, the ML models predicted more accurately than the DD method, especially for the heating energy use prediction. Furthermore, the DD method uncertainty was 1–4.5 % lower in 2020, which means the difference reached up to 36 % and 43 % between the two years, respectively, for heating and electricity energy use.

Although the results in Fig. 15 show good accuracy of each method and building, the RB2 electricity energy use model prediction uncertainty was lower. This is explained by the fact that the electricity energy use of RB2 had a small correlation while RB1 had no correlation with outdoor temperature (Fig. 12 and Figure A.1 in Appendix A).

The monthly assessments revealed the differences more precisely. This assessment was conducted using monthly percentage error metrics and is outlined in Appendix B. The model prediction percentage error was higher in summer months in 2021. The DD method showed high overestimation (about 2 times) in RB2 in June and July. Compared to the DD method, the ML method had minor percentage error in June 2020 and July 2021. As in 2021 the CDD-s and direct solar radiation were higher, the high percentage error in the monthly method could be caused by normalisation. This also causes the difference in CV(RMSE) among these years. The ML method is more accurate due to used independent variables like hourly outdoor temperature and solar radiation. In contrast, in electricity energy use prediction, the error was smaller and did not appear to be dependent on the season. The ML method will be well appropriate for monthly baseline prediction and savings calculation. However, when presenting the monthly savings calculated with the DD method, the monthly percentage error of the prediction model should be presented side by side with the energy-saving report to show the sensitivity of savings calculations. Furthermore, this study assumes, that the energy meter is read at the end of month. This is normal trend but not common standard. Therefore, the data should be pre-processed before using this monthly DD method.

3.2. The uncertainty of the annual prediction methods in different periods

3.2.1. Pre-COVID period (2017–2019)

The RB2 metered energy use from 2017 to 2018 was used for model training or to derive the baseline for prediction. Then the models were used to predict the energy use in 2019, utilising the model input described in the methods. Heating and electricity energy use prediction uncertainty results are compared in the following Fig. 16 and in Table 7-Table 8 for each method.

In RB2 the DD model heating prediction CV(RMSE) was 19.3 %, for the hourly ML with RF the CV(RMSE) was 16.7 %, and with NN it was 17.5 %. The DD model electricity prediction CV(RMSE) was 6.91 %, while for the ML with RF the CV(RMSE) was 6.18 %, and with NN it was 6.11 %. However, the metered energy use in October–December 2019 was about 20 % and 8 % higher than predicted, respectively, for heating and electricity (Fig. 16). Therefore, we could assume that this period had some anomalies arising from external factors (the authors do not know the exact reason). Excluding October–December from the CV(RMSE) calculation, the uncertainty became lower, about 46–48 % and 10–21 %, respectively, for heating and electricity. The uncertainty results with metered data from January–September 2019 are outlined in Fig. 17. In contrast to the validation phase heating energy use uncertainty, the difference is minor between DD and ML method prediction with metered data. The electricity energy use predictions uncertainty does not differ much between methods.

3.2.2. COVID period (2020–2022)

The energy use prediction analysis during the COVID-19 period and after reveals different aspects. The results are concluded in Table 9 and detailed results are in Appendix C.

Considering the heating energy use prediction, in RB1, the annual prediction uncertainty was very high (30–40 %), as well as the monthly percentage error (Table C.1 in Appendix C). This was caused by the noticeable decrease in heating energy use in recent years, as can be seen in Fig. 18. Therefore, there is a need for the detection of unusual changes in energy use, which means the methods for dynamic normalisation, anomalies detection and estimating the weather independent energy use. In contrast, in RB2 the uncertainty of the annual heating prediction was lower than in the pre-COVID period. However, monthly, the percentage error was very high for the DD model (Table C.2 in Appendix C).

The annual performance was better for electricity energy use prediction, but still the CV(RMSE) was about 1.5–2.5 % higher than in the pre-COVID period for RB2. Analysing the monthly percentage error, it varied over the year for each method (Table C.3 and C.4 in

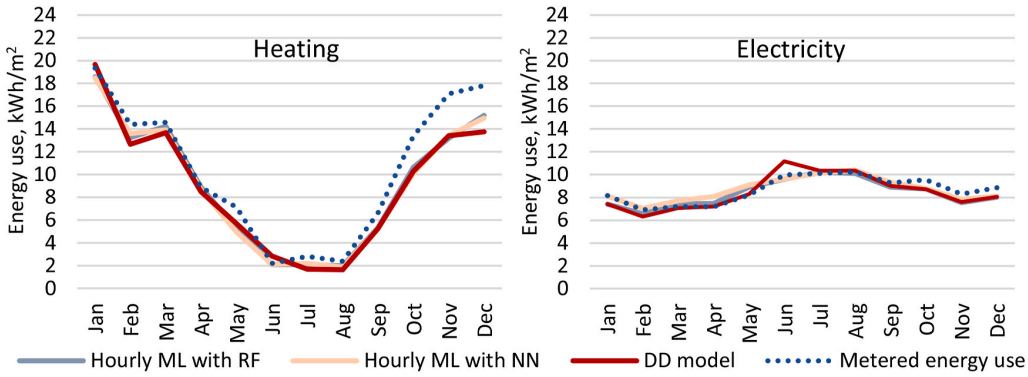


Fig. 16. Metered heating and electricity energy use compared with three different model prediction in 2019 in RB2.

Table 7
Metered heating energy use in kWh/m2 compared with three different model prediction for 2019 in RB2.

Units: kWh/m^2	Metered energy use	DD model		Hourly ML model (Random Forest)		Hourly ML model (Neural Network)	
Month		Prediction	Percentage error, %	Prediction	Percentage error, %	Prediction	Percentage error, %
Jan-19	19.33	19.6	−1.6	18.57	3.9	18.5	4.5
Feb-19	14.38	12.7	12.0	13.24	7.9	13.6	5.5
Mar-19	14.57	13.7	6.3	14.23	2.3	13.9	4.6
Apr-19	8.86	8.5	4.1	8.89	−0.4	8.7	2.0
May-19	7.12	5.7	19.9	5.24	26.4	5.0	30.3
Jun-19	2.19	2.9	−30.1	2.11	4.0	2.1	3.5
Jul-19	2.81	1.7	39.1	2.10	25.1	2.2	21.7
Aug-19	2.40	1.7	31.2	2.00	16.8	1.9	21.6
Sep-19	6.61	5.3	20.5	5.31	19.6	5.2	20.6
Oct-19	13.38	10.3	23.1	10.63	20.5	10.1	24.5
Nov-19	17.08	13.4	21.6	13.18	22.8	13.4	21.3
Dec-19	17.78	13.8	22.7	15.18	14.6	15.0	15.9
Total	**126.5**	**109.1**	**13.79**	110.7	**12.51**	109.5	**13.44**
MAPE, %			**19.34**		**13.71**		**14.68**
R^2		0.89		0.91		0.91	
RMSE (kWh/m^2)		2.03		1.76		1.85	
NMBE		13.8 %		12.5 %		13.4 %	
CV(RMSE)		**19.3 %**		**16.7 %**		**17.5 %**	

Table 8
Metered electricity energy use in kWh/m2 compared with three different model prediction for 2019 in RB2.

Units: kWh/m^2	Metered energy use	DD model		Hourly ML model (Random Forest)		Hourly ML model (Neural Network)	
Month		Prediction	Percentage error, %	Prediction	Percentage error, %	Prediction	Percentage error, %
Jan-19	8.16	7.4	9.3	7.42	9.1	8.1	0.6
Feb-19	6.92	6.3	8.5	6.56	5.1	7.0	−1.8
Mar-19	7.21	7.1	2.1	7.45	−3.2	7.7	−7.0
Apr-19	7.17	7.2	−0.4	7.47	−4.1	8.1	−12.7
May-19	8.22	8.3	−0.9	8.91	−8.4	9.1	−10.7
Jun-19	9.97	11.2	−12.1	9.59	3.8	9.6	3.4
Jul-19	10.09	10.4	−2.6	10.20	−1.1	10.1	−0.5
Aug-19	10.23	10.4	−1.3	10.12	1.1	10.4	−1.7
Sep-19	9.28	9.0	2.7	8.91	4.0	9.3	−0.7
Oct-19	9.55	8.7	8.6	8.76	8.3	8.8	8.1
Nov-19	8.29	7.6	8.2	7.56	8.8	7.8	5.5
Dec-19	8.84	8.1	8.8	8.03	9.2	8.1	8.2
Total	**103.9**	**101.6**	**2.23**	**101.0**	**2.86**	**104.3**	**−0.36**
MAPE, %			**5.46**		**5.52**		**5.08**
R^2		0.72		0.78		0.78	
RMSE (kWh/m^2)		0.60		0.53		0.53	
NMBE		2.23 %		2.86 %		−0.36 %	
CV(RMSE)		**6.91 %**		**6.18 %**		**6.11 %**	

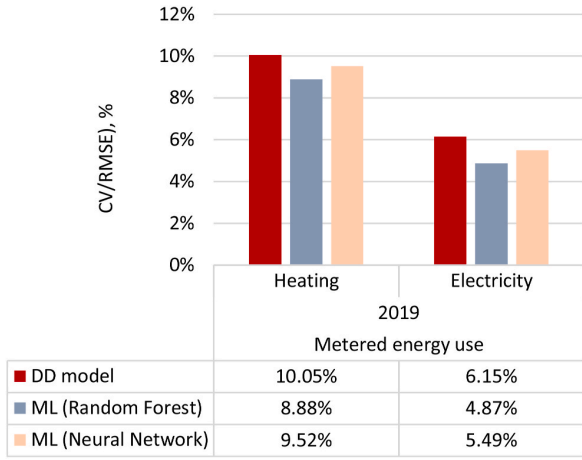


Fig. 17. The uncertainty metric CV(RMSE) of prediction models in RB2 excluding high energy use period (Oct–Dec 2019; i.e., calculation for 9 months).

Table 9
Models' predictions uncertainty results in COVID period.

Energy	Reference building	CV(RMSE)		
		DD model	ML (Random Forest)	ML (Neural Network)
Heating	RB1 – school	33 %	30 %	40 %
	RB2 – office	11.5 %	11.6 %	12.1 %
Electricity	RB1 – school	11.5 %	9.0 %	9.4 %
	RB2 – office	8.4 %	8.6 %	8.4 %

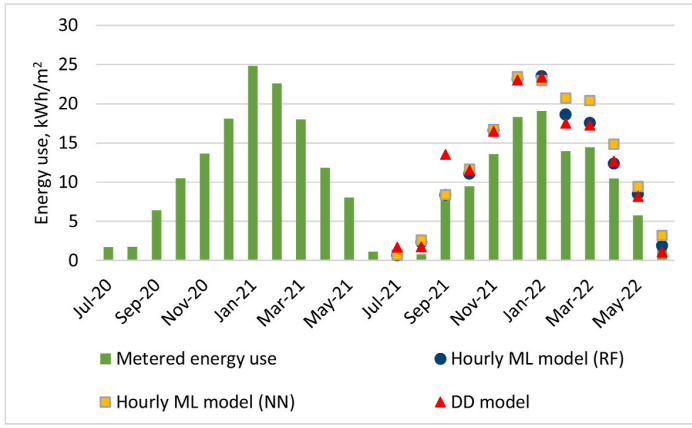


Fig. 18. Metered and predicted heating energy use in RB1.

Appendix C), more for RB1 and the DD method. However, excluding the RB1 COVID period heating energy use prediction, the CV (RMSE) was generally 11.5–19.3 % and 6.91%–11.5 %, respectively, for heating and electricity energy use.

Excluding the RB1 COVID period analysis, the previous results satisfied the ASHRAE Guideline requirements for annual baseline prediction for monthly saving calculation. However, the monthly assessment confirms that the ML method is more accurate in monthly-based heating baseline predictions.

There is few research found on energy use prediction on a monthly scale. For comparison, the percentage error found in this study is about 5%–9% for electricity energy use prediction, which is a bit higher than that of Dong et al. result (<5 %). Considering heating energy use prediction, there was no reference found for comparison. Therefore, this study could be a good reference to enhance the monthly energy use baseline derivation and evaluate the accuracy for saving qualification. However, there is a need for further research analysing the weather and building usage impact on actual energy use in commercial buildings to improve baseline

derivation.

3.3. ML approach highlights

3.3.1. Clustering results

As mentioned earlier, the clustering phase was included into the approach to address seasonal variations. The idea was to form clusters based on temporal and environmental independent variables, allowing the model to capture the varying conditions that influence energy use. These clusters allowed to train and validate several regression models on subsets of energy use data specific to each cluster. The following Tables D.1 and D.2 in Appendix D reveal the clusters by showing the proportions of features' values included in each cluster relative to the total number of observations in the training set. The selected independent features were used to account for potential differences in conditions associated with different energy types, with a focus on solar irradiance during transitional periods in spring and autumn, and specific enthalpy of air, as both can affect thermal comfort and energy use for heating as well as cooling (as part of total electricity energy use).

Based on these visual representations, we analysed and described the clusters, which helped us understand how each regression model focused on capturing energy use behavior under specific conditions. The descriptions are provided in the following Table 10. It is evident that solar-related features add valuable description to the clusters and including such features is beneficial. However, it is worth considering whether using alternative variable combinations, e.g. outdoor air temperature, sun position, and cloud coverage, could provide similar results, especially when solar irradiance data is not available.

3.3.2. Hourly energy use prediction performance

Although the scope of this study was the monthly energy use estimation, Table 11 outlines the hourly prediction performance of the ML method. It shows the prediction errors relative to metered data using several statistical indicators – MAE, RMSE, CVRMSE, and RMSLE, as used in GEPIII [25] to set the first benchmarks for such tasks, accounting for different scales of energy use in various applications.

The performance aligned with findings from existing literature. The comparison periods for hourly predictions are the same as for the monthly comparison of metered energy use (for RB2 only for 2017–2019). The uncertainty for the hourly heating energy use prediction exceeded 60 % in RB1 cases. However, in RB2 during the training period (2019), the uncertainty of prediction was around 27 %, and in the validation period it was 33 %. Gunay et al. [13] reported CV(RMSE) of 3–16 % during the training period using artificial neural network (ANN) method. Compared to the Random Forest electricity use prediction models during the validation period, the method in this study had uncertainty ranging from 22.6 to 31.6 %. However, Anand et al. [32] conducted a study that showed uncertainty as 35.3 %.

There is also a difference in the RMSLE scores between the GEPIII competition [25] and those in Table 11, which may be due to the decision to train building-specific regression models, despite applying the same clusters identified using independent variables. The performance improvement may also come from addressing both seasonal and temporal changes, which were grouped into similar conditions, via, again, clustering.

Before employing these models for hourly estimations, further development is necessary. The current models have shown strong performance and are particularly suitable for monthly scale analysis with aggregated hourly estimations. In order to enhance the effectiveness of the models', it is crucial to include an additional step focused on optimizing models' hyperparameters. Such optimization aims to find a balance between avoiding overfitting and accurately capturing the behaviour in the data.

However, including fine-tuning and optimization steps demands significant computational power and increase execution time. In such cases, building a generalizing model may be more practical. A generalizing model, while more efficient, does not allow for the application of same-condition clusters of energy use, as the buildings could be located in different locations and climatic zones. Nevertheless, the clustering step has proven to be efficient in addressing seasonal variations, ensuring that a suitable model is used depending on environmental conditions at a certain time.

Table 10
Clusters' description.

	Targeting heating energy use estimations	Targeting electricity energy use estimations
Cluster	Cluster description	Cluster description
0	Warm, sunny conditions during daytime hours in generally warmer months, characterized by high to moderate temperatures and high solar irradiance.	Warm, humid conditions during nighttime, mornings, and evenings in summer and transitional months, characterized by moderate temperatures and low to moderate solar irradiance. Cooling needs are driven by the high enthalpy.
1	Cooler conditions during daytime hours in transitional and winter months, characterized by moderate to low temperatures and moderate solar irradiance.	Cold, humid conditions throughout the day during winter months, characterized by moderate to low solar irradiance and moderate to cold temperatures.
2	Cooler conditions during nighttime and early morning hours in the warm months, characterized by high to moderate temperatures and moderate to low solar irradiance.	Warm, dry conditions in the afternoon during the warmer months, characterized by strongly sunny weather. Cooling needs are driven primarily by solar heat gain.
3	Cold conditions during nighttime and early morning hours in winter and transitional months, characterized by moderate to low temperatures and minimal solar irradiance.	–

Table 11
The overall performance of the ML method, compared to metered data from RB1 (period from July 2020 to July 2022) and RB2 (period 2017–2019).

RB1	Heating				Electricity			
	RF		NN		RF		NN	
	Training	Validation	Training	Validation	Training	Validation	Training	Validation
MAE	0.90	4.89	2.66	5.75	0.66	2.88	2.08	2.70
RMSE	1.40	6.96	3.88	8.15	1.02	3.70	2.85	3.53
CV-RMSE	8.85 %	52.70 %	24.52 %	61.88 %	8.09 %	29.28 %	22.64 %	27.93 %
RMSLE	0.19	0.56	0.42	0.63	0.08	0.26	0.2	0.25
RB2	**Heating**				**Electricity**			
	RF		NN		RF		NN	
	Training	Validation	Training	Validation	Training	Validation	Training	Validation
MAE	1.01	3.77	2.62	3.73	0.89	2.91	2.63	2.81
RMSE	1.38	4.85	3.54	4.77	1.31	3.99	3.64	3.88
CV-RMSE	10.57 %	33.57 %	27.07 %	33.01 %	11.33 %	33.65 %	31.56 %	32.72 %
RMSLE	0.2	0.56	0.43	0.56	0.12	0.31	0.29	0.3

4. Conclusion

In both renovation projects and the application of minimum energy performance standards, it is important to be able to verify achieved energy savings. Therefore, it is necessary to establish an accurate energy use baseline to assess the changes in energy use resulting from building renovation. In contrast to many studies, in which short-term energy use forecasts are discussed, this study used hourly and monthly full-year historic metered and simulated data of heating and electricity energy use to predict monthly energy use in the post-retrofit year (the past or the current year). We compared the performance of the two proposed methods against existing criteria, using both simulated and metered data of heating and electricity energy use in baseline generation. The first method was based on monthly degree-days normalisation and baseline derivation (DD) and required monthly energy bill data. The second method utilised machine learning (ML) techniques, including clustering and non-linear regression models (random forest and neural network) and required hourly energy use data as one of the inputs. The comparative analysis of these methods was conducted using CV(RMSE) as a statistical indicator, computed over a one-year period. The methods were first validated using data from two simulation models, where building use is defined during model setup and calibration. The methods' applicability was then assessed using metered data from the reference buildings from two different periods. The validation of the methods showed low uncertainty on a monthly scale, achieving CV(RMSE) from 4.6 to 10.4 % and from 1.4 to 7.5 %, for DD and ML method respectively. When comparing the machine learning models, the neural network (NN) model slightly outperformed the random forest (RF) model during validation with simulation data. However, the opposite was observed during the applicability analysis with metered data. Additionally, here the results showed a significant difference between buildings and calculation periods. During the COVID-19 period (2020–2022), the models' prediction uncertainty for heating energy use in reference building 1 was unsuitable, with CV(RMSE) values ranging between 30 and 40 %. However, the predictions for electricity energy use were more accurate, with CV(RMSE) values of 9–11.5 %. In reference building 2, the CV(RMSE) values for heating energy use prediction were below 12 %. In the pre-COVID period (year 2019), the heating energy predictions CV(RMSE) were higher by nearly 5–8% due to energy use increase towards the end of the year. For electricity use predictions in the COVID-2019 period, the CV(RMSE) values were between 8.4 and 8.6 % in reference building 2. The uncertainty was about 1.5–2.5 % lower in 2019. The machine learning methods with RF and NN proved to be suitable for monthly heating and electricity energy use prediction in the studied cases. The DD method also provided an accurate quick check or solution in cases when only monthly data is available. However, it is suggested to present monthly percentage error of the predictions from DD model side by side with the energy-saving report. Additionally, tailoring ML models' parameters is necessary to avoid models replicating training period data. Furthermore, the integration of specialized feature evaluation metrics can be proposed, each suited for unsupervised and supervised learning, to optimize feature selection. Additionally, this study showed that it is essential to further investigate the energy prediction methods applicability with actual metered data. This study contributes to the assessment of renovation impact and operational energy savings by offering additional perspectives on selecting energy use modelling methods, which are also applicable in the context of Minimum Energy Performance Standards.

CRediT authorship contribution statement

Helena Kuivjõgi: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Sofia Vasman:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Eduard Petlenkov:** Writing – review & editing, Validation, Supervision, Software, Resources, Project administration, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Martin Thalfeldt:** Writing – review & editing, Validation, Supervision, Software, Resources, Project administration, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Jarek Kurnitski:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A

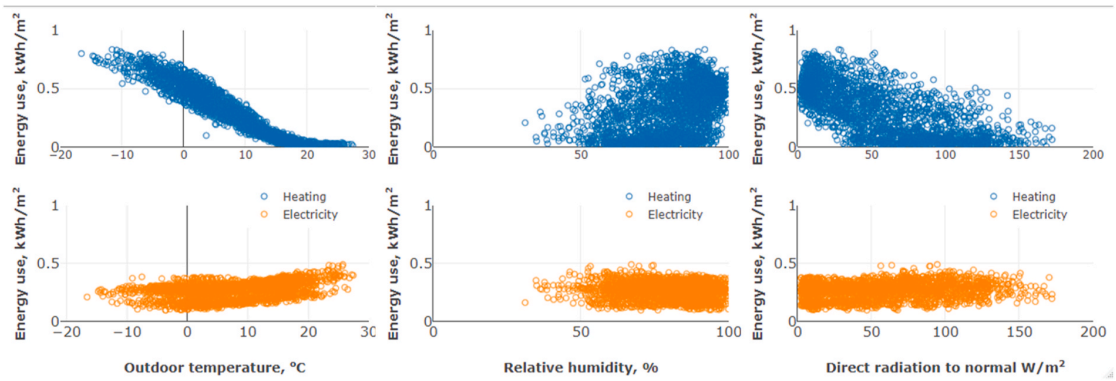


Fig. A.1. RB2 metered heating (blue) and electricity (orange) daily energy use (kWh/m^2) in 2017–2023 with actual weather data in this period.

Appendix B. validation of prediction methods utilising simulation data

Table B.1
Simulation model heating energy use in kWh/m^2 compared with three different model prediction for 2020 and 2021 in RB1. The negative percentage error show, that the prediction model overestimates the energy use and vice versa.

Units: kWh/m^2	Simulation energy use		DD model				Hourly ML model (Random Forest)				Hourly ML model (Neural Network)			
Month			Prediction		Percentage error, %		Prediction		Percentage error, %		Prediction		Percentage error, %	
	2020	2021	2020	2021	2020	2021	2020	2021	2020	2021	2020	2021	2020	2021
Jan	16.8	22.3	15.7	22.1	6.5	0.8	16.8	22.3	0.0	0.1	16.9	22.4	−0.6	−0.4
Feb	17.3	22.8	16.7	23.3	3.4	−1.9	17.4	22.3	−0.8	2.1	17.7	22.9	−2.2	−0.5
Mar	16.4	19.1	16.8	19.0	−2.6	0.7	16.9	18.9	−3.0	1.2	16.7	19.1	−2.2	0.3
Apr	13.1	13.4	13.0	13.3	0.1	0.8	13.0	13.2	0.2	1.2	13.2	13.4	−0.9	−0.3
May	8.5	7.9	7.7	7.0	9	12	8.5	7.7	0.9	3.6	8.3	7.8	2.4	2.1
Jun	2.3	1.6	2.7	2.7	−14	−63	2.2	1.7	6.1	−3.8	2.1	1.6	11.5	2.7
Jul	2.7	1.2	2.6	2.6	1.5	−121	2.8	1.4	−5.5	−14.5	2.6	1.3	1.6	−10.4
Aug	2.4	3.1	2.4	2.4	2.4	23	2.4	3.0	0.1	2.8	2.4	3.0	0.5	3.8
Sep	4.4	7.5	4.1	7.0	7.3	6.6	4.3	7.2	2.0	4.1	4.4	7.4	0.3	1.4
Oct	9.7	10.4	9.4	10.3	2.6	0.9	10.0	10.6	−3.2	−2.4	10.2	10.7	−5.3	−3.7
Nov	14.0	16.3	13.9	16.6	0.9	−2.0	14.4	16.4	−2.4	−0.7	14.5	16.6	−3.1	−1.6
Dec	18.3	21.9	18.0	22.7	1.5	−3.6	17.3	22.0	5.3	−0.1	18.0	22.2	1.7	−1.0

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Table B.1 (*continued*)

Units: kWh/m^2	Simulation energy use		DD model				Hourly ML model (Random Forest)				Hourly ML model (Neural Network)			
Month			Prediction		Percentage error, %		Prediction		Percentage error, %		Prediction		Percentage error, %	
	2020	2021	2020	2021	2020	2021	2020	2021	2020	2021	2020	2021	2020	2021
Total	**125.9**	**147.6**	**123.1**	**148.9**	**2.24**	**−0.90**	**126.1**	**146.6**	**−0.10**	**0.64**	**127.0**	**148.3**	**−0.84**	**−0.52**
MAPE, %					**4.35**	**19.72**			**2.46**	**3.06**			**2.70**	**2.36**
R^2			0.99	0.99			0.997	0.999			0.998	1.000		
RMSE (kWh/m^2)			0.48	0.69			0.35	0.23			0.28	0.17		
NMBE			2.24 %	−0.90 %			−0.10 %	0.64 %			−0.84 %	−0.52 %		
CV(RMSE)			**4.55 %**	**5.62 %**			**3.32 %**	**1.84 %**			**2.69 %**	**1.41 %**		

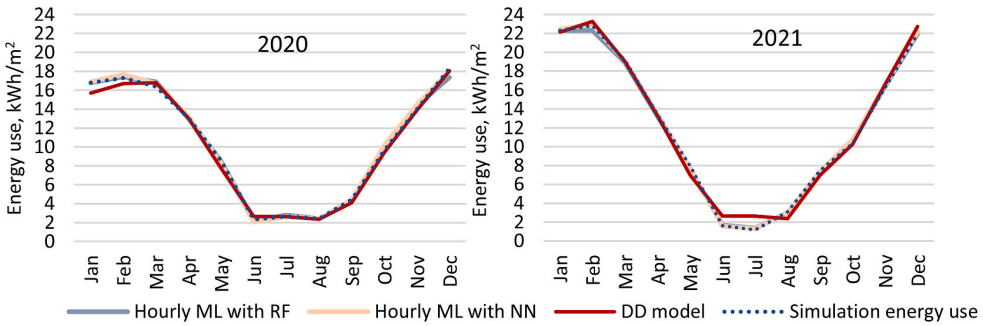


Fig. B.1. Simulation model heating energy use compared with three different model prediction for 2020 and 2021 in RB2.

Table B.2
Simulation model heating energy use in kWh/m^2 compared with three different model prediction for 2020 and 2021 in RB2. The negative percentage error show, that the prediction model overestimates the energy use and vice versa.

Units: kWh/m^2	Simulation energy use		DD model				Hourly ML model (Random Forest)				Hourly ML model (Neural Network)			
Month			Prediction		Percentage error, %		Prediction		Percentage error, %		Prediction		Percentage error, %	
	2020	2021	2020	2021	2020	2021	2020	2021	2020	2021	2020	2021	2020	2021
Jan	13.2	18.7	13.2	18.6	0.1	0.8	13.3	18.6	−0.9	0.7	13.1	18.4	0.5	1.9
Feb	13.3	18.2	13.1	18.2	1.3	0.2	13.2	18.2	0.4	−0.3	13.0	17.8	1.8	2.1
Mar	12.0	14.1	12.5	14.1	−4.8	−0.4	12.3	14.3	−2.8	−1.7	12.0	14.0	−0.3	0.8
Apr	8.8	9.1	8.9	9.1	−1.1	0.4	9.1	9.2	−3.6	−1.0	8.9	9.2	−1.5	−0.6
May	7.7	7.5	6.5	5.8	17	22	7.2	6.9	7.3	8.5	7.6	7.0	2.3	6.5
Jun	2.6	1.6	3.3	3.3	−26	−99	2.5	1.7	3.2	−2.3	2.5	1.7	5.2	−4.2
Jul	2.7	1.0	2.5	2.5	8.0	−164	2.7	1.0	0.9	−5.1	2.6	1.0	4.1	−3.0
Aug	2.6	3.6	2.5	2.5	3.9	29	2.5	3.2	3.4	9.8	2.5	3.0	5.9	14.8
Sep	2.5	4.6	2.8	4.2	−12.3	8.8	2.7	4.7	−8.8	−0.7	2.7	4.6	−7.4	0.6
Oct	6.8	7.1	6.8	7.3	0.5	−2.8	7.0	7.3	−2.3	−2.8	6.9	7.3	−1.6	−2.2
Nov	10.6	12.4	10.6	12.6	0.4	−1.1	10.8	12.8	−2.2	−2.5	10.8	12.6	−1.5	−1.4
Dec	15.9	19.8	16.1	20.3	−1.3	−2.5	16.2	20.3	−1.7	−2.3	16.0	20.2	−0.4	−1.8
Total	**98.8**	**117.8**	**98.8**	**118.5**	**0.01**	**−0.67**	**99.6**	**118.1**	**−0.87**	**−0.31**	**98.6**	**116.7**	**0.21**	**0.88**
MAPE, %					**6.38**	**27.62**			**3.13**	**3.15**			**2.72**	**3.33**
R^2			0.99	0.98			0.997	0.998			0.999	0.998		
RMSE (kWh/m^2)			0.47	0.89			0.25	0.28			0.14	0.29		
NMBE			0.01 %	−0.67 %			−0.87 %	−0.31 %			0.21 %	0.88 %		
CV(RMSE)			**5.75 %**	**9.04 %**			**3.07 %**	**2.90 %**			**1.74 %**	**2.92 %**		

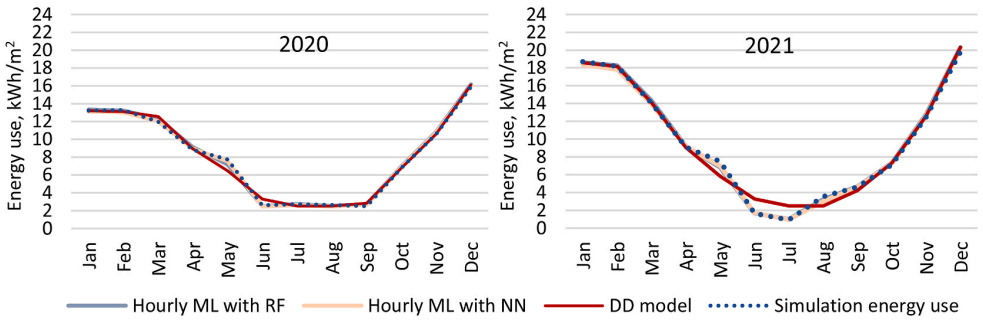


Fig. B.2. Simulation model heating energy use compared with three different model prediction for 2020 and 2021 in RB2.

Table B.3
Simulation model electricity energy use in kWh/m^2 compared with three different model prediction for 2020 and 2021 in RB1. The negative percentage error show, that the prediction model overestimates the energy use and vice versa.

Units: kWh/m^2	Simulation energy use		DD model				Hourly ML model (Random Forest)				Hourly ML model (Neural Network)			
			Prediction		Percentage error, %		Prediction		Percentage error, %		Prediction		Percentage error, %	
Month	2020	2021	2020	2021	2020	2021	2020	2021	2020	2021	2020	2021	2020	2021
Jan	3.3	3.1	3.2	3.2	2.7	−5.4	3.4	3.3	−1.2	−6.0	3.3	3.3	0.6	−8.4
Feb	3.0	3.0	3.0	3.0	1.5	−1.7	3.1	2.9	−0.9	0.1	3.3	3.2	−9.4	−9.5
Mar	3.3	3.5	3.3	3.3	0.3	3.8	3.3	3.3	1.1	5.1	3.4	3.5	−1.2	−2.2
Apr	3.3	3.3	3.2	3.2	3.8	3.8	3.2	3.1	4.1	6.6	3.2	3.3	3.1	1.9
May	3.2	3.4	3.6	3.3	−12.3	0.2	3.5	3.5	−7.3	−3.0	3.2	3.2	0.1	4.5
Jun	3.1	3.2	2.9	3.0	5.4	8.8	2.9	3.3	4.5	−0.4	2.8	3.2	7.1	1.6
Jul	2.7	4.1	2.9	3.0	−8.0	25.4	2.7	3.6	−0.4	12.4	2.8	3.8	−4.7	7.3
Aug	3.1	3.0	3.5	3.3	−10.5	−10.4	3.3	3.2	−5.8	−6.9	3.6	3.3	−13.1	−10.3
Sep	3.4	3.3	3.4	3.3	−0.1	1.2	3.2	3.2	6.4	3.5	3.4	3.2	1.2	3.5
Oct	3.3	3.2	3.4	3.4	−2.6	−6.9	3.2	3.3	4.4	−3.1	3.4	3.3	−0.4	−3.7
Nov	3.2	3.3	3.3	3.3	−2.8	1.3	3.1	3.2	3.3	3.8	3.2	3.3	0.5	2.1
Dec	3.2	3.2	3.0	3.0	6.9	5.7	2.8	2.6	10.9	16.4	3.0	2.8	7.6	12.7
Total	**38.3**	**39.6**	**38.8**	**38.5**	**−1.19**	**2.78**	**37.7**	**38.5**	**1.66**	**2.68**	**38.5**	**39.5**	**−0.61**	**0.27**
MAPE, %					**4.74**	**6.22**			**4.20**	**5.61**			**4.08**	**5.65**
R^2			0.04	−0.52			0.26	0.21			0.13	0.39		
RMSE (kWh/m^2)			0.19	0.34			0.17	0.25			0.18	0.22		
NMBE			−1.19 %	2.78 %			1.66 %	2.68 %			−0.61 %	0.27 %		
CV(RMSE)			**5.92 %**	**10.38 %**			**5.22 %**	**7.50 %**			**5.64 %**	**6.55 %**		

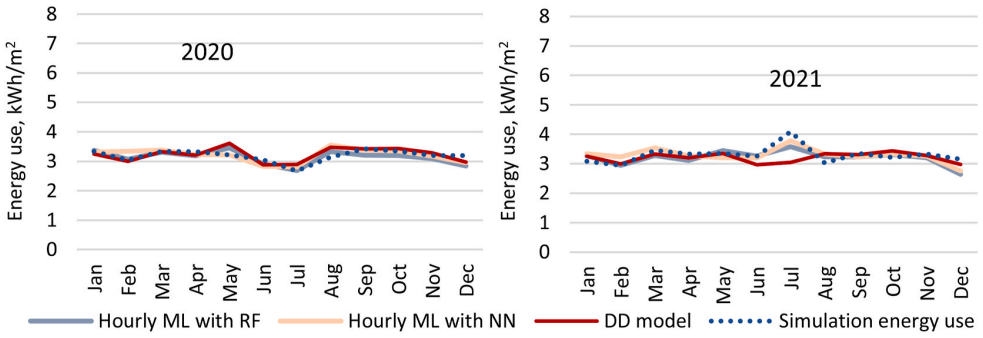


Fig. B.3. Simulation model electricity energy use compared with three different model prediction for 2020 and 2021 in RB1.

Table B.4
Simulation model electricity energy use in kWh/m^2 compared with three different model prediction for 2020 and 2021 in RB2. The negative percentage error show, that the prediction model overestimates the energy use and, vice versa.

Units: kWh/m^2	Simulation energy use		DD model				Hourly ML model (Random Forest)				Hourly ML model (Neural Network)			
Month			Prediction		Percentage error, %		Prediction		Percentage error, %		Prediction		Percentage error, %	
	2020	2021	2020	2021	2020	2021	2020	2021	2020	2021	2020	2021	2020	2021
Jan	4.8	4.5	4.8	4.8	1.2	−6.1	4.9	4.7	−0.9	−4.2	4.7	4.7	2.4	−4.1
Feb	4.3	4.2	4.2	4.2	0.9	−0.1	4.3	4.2	−0.1	0.7	4.4	4.3	−2.9	−2.6
Mar	4.7	4.8	4.7	4.7	0.7	3.3	4.6	4.5	1.3	6.1	4.6	4.6	1.4	4.2
Apr	4.7	4.7	4.6	4.6	2.5	2.3	4.5	4.4	4.8	5.8	4.5	4.5	4.0	5.0
May	4.7	4.9	5.3	5.1	−12.3	−4.8	5.0	5.0	−5.7	−3.8	5.1	5.3	−7.3	−8.7
Jun	5.8	6.8	5.7	6.0	2.7	10.9	5.5	6.1	5.0	10.1	5.7	6.4	2.4	6.0
Jul	5.6	7.8	5.7	6.7	−1.2	13.9	5.4	7.1	4.1	8.9	5.6	7.4	1.4	4.7
Aug	5.4	5.1	5.8	5.6	−8.0	−9.7	5.5	5.3	−1.9	−3.4	5.8	5.4	−6.9	−6.5
Sep	4.9	4.7	4.8	4.7	2.3	0.1	4.6	4.6	5.5	3.4	4.8	4.5	1.8	4.5
Oct	4.7	4.5	4.8	4.8	−1.9	−5.4	4.6	4.7	2.4	−3.6	4.5	4.5	3.5	0.6
Nov	4.5	4.6	4.6	4.6	−2.4	1.3	4.3	4.5	3.1	2.8	4.5	4.5	0.1	2.6
Dec	4.8	4.8	4.5	4.5	5.7	6.0	4.4	4.1	7.8	14.4	4.5	4.2	7.3	12.4
Total	**59.0**	**61.5**	**59.5**	**60.3**	**−0.83**	**1.93**	**57.7**	**59.2**	**2.18**	**3.66**	**58.6**	**60.3**	**0.61**	**1.81**
MAPE, %					**3.48**	**5.32**			**3.54**	**5.61**			**3.45**	**5.15**
R^2			0.72	0.81			0.78	0.85			0.79	0.91		
RMSE (kWh/m^2)			0.24	0.43			0.21	0.38			0.21	0.31		
NMBE			−0.83 %	1.93 %			2.18 %	3.66 %			0.61 %	1.81 %		
CV(RMSE)			**4.85 %**	**8.48 %**			**4.25 %**	**7.48 %**			**4.21 %**	**6.03 %**		

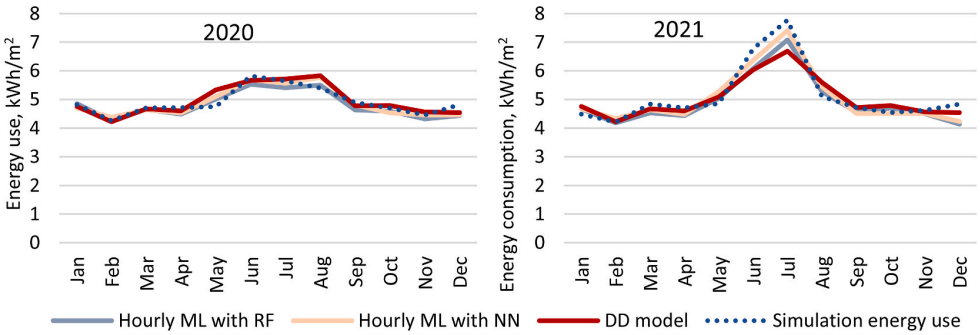


Fig. B.4. Simulation model electricity energy use compared with three different model prediction for 2020 and 2021 in RB2.

Appendix C

The energy use analysis after COVID-19 was based on metered data from July 2020 to July 2022. The model was derived and trained with data from July 2020 to July 2021. The model's prediction was compared with the monthly metered energy use of the period from July 2021 to July 2022.

Table C.1
Metered heating energy use in kWh/m^2 compared with three different model prediction for period from July 2021 to July 2022 in RB1. The negative percentage error show, that the prediction model overestimates the energy use and vice versa.

Units: kWh/m^2	Metered energy use	DD model		Hourly ML model (Random Forest)		Hourly ML model (Neural Network)	
Month		Prediction	Percentage error, %	Prediction	Percentage error, %	Prediction	Percentage error, %
Jan-22	19.10	23.4	−22.5	23.55	−23.3	23.0	−20.3
Feb-22	13.95	17.5	−25.6	18.63	−33.6	20.7	−48.6
Mar-22	14.46	17.3	−19.3	17.56	−21.4	20.4	−41.1
Apr-22	10.45	12.7	−21.5	12.36	−18.2	14.8	−42.0
May-22	5.75	8.2	−41.8	8.50	−47.8	9.4	−64.2
Jun-22	1.89	1.1	41.5	1.89	0.2	3.2	−70.0
Jul-21	0.24	1.7	−608.0	0.66	−172.4	0.7	−184.8
Aug-21	0.79	1.8	−123.3	2.32	−194.7	2.6	−232.3
Sep-21	7.72	13.5	−75.3	8.36	−8.3	8.4	−8.8
Oct-21	9.46	11.5	−21.8	11.07	−17.0	11.7	−23.3
Nov-21	13.58	16.5	−21.3	16.60	−22.2	16.7	−23.0

(*continued on next page*)

Table C.1 (*continued*)

Units: kWh/m^2	Metered energy use	DD model		Hourly ML model (Random Forest)		Hourly ML model (Neural Network)	
Month		Prediction	Percentage error, %	Prediction	Percentage error, %	Prediction	Percentage error, %
Dec-21	18.33	23.0	−25.6	23.15	−26.3	23.5	−28.0
Total	**115.7**	**148.2**	**−28.04**	**144.6**	**−24.99**	**155.2**	**−34.07**
MAPE, %			**87.31**		**48.78**		**65.53**
R^2		0.74		0.79		0.62	
RMSE (kWh/m^2)		3.19		2.89		3.83	
NMBE		−28 %		−25 %		−34 %	
CV(RMSE)		**33 %**		**30 %**		**40 %**	

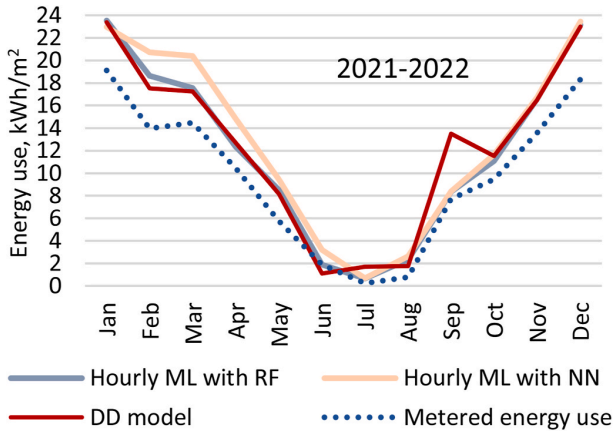


Fig. C.1. Metered heating energy use compared with three different model prediction for 2021-07 to 2022-07 in RB1. The peak in September is caused by the colder month – more HDDs than last September.

Table C.2
Metered heating energy use in kWh/m^2 compared with three different model prediction for period from July 2021 to July 2022 in RB2. The negative percentage error show, that the prediction model overestimates the energy use and vice versa.

Units: kWh/m^2	Metered energy use	DD model		Hourly ML model (Random Forest)		Hourly ML model (Neural Network)	
Month		Prediction	Percentage error, %	Prediction	Percentage error, %	Prediction	Percentage error, %
Jan-22	18.51	16.8	9.2	17.10	7.6	17.1	7.3
Feb-22	15.34	13.2	14.1	13.56	11.6	14.1	8.1
Mar-22	13.57	12.8	5.9	13.37	1.5	15.2	−12.0
Apr-22	10.01	11.2	−11.5	10.78	−7.7	11.7	−17.3
May-22	5.47	6.4	−17.9	6.53	−19.3	6.5	−18.9
Jun-22	1.91	1.0	47.8	1.42	25.7	1.9	0.0
Jul-21	0.65	1.5	−125.2	0.91	−38.9	0.7	−9.7
Aug-21	2.39	1.4	43.0	2.01	16.1	2.4	−1.2
Sep-21	6.75	7.8	−15.7	5.65	16.4	5.9	12.3
Oct-21	9.55	8.7	8.9	8.46	11.5	8.3	12.9
Nov-21	14.13	13.3	5.6	12.85	9.1	13.0	8.4
Dec-21	20.71	20.6	0.7	18.61	10.2	18.8	9.2
Total	**119.0**	**114.6**	**3.70**	**111.2**	**6.53**	**115.7**	**2.74**
MAPE, %			**25.47**		**14.62**		**9.77**
R^2		0.97		0.97		0.96	
RMSE (kWh/m^2)		1.14		1.15		1.20	
NMBE		4 %		7 %		3 %	
CV(RMSE)		**11.5 %**		**11.6 %**		**12.1 %**	

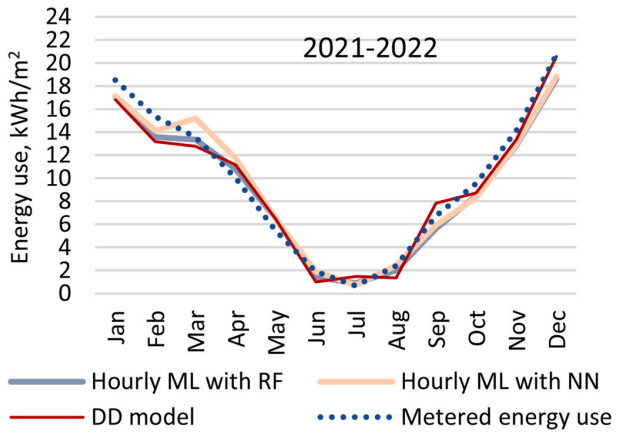


Fig. C.2. Metered heating energy use compared with three different model prediction for 2021-07 to 2022-07 in RB2.

Table C.3
Metered electricity energy use in kWh/m^2 compared with three different model prediction for period from July 2021 to July 2022 in RB1. The negative percentage error show, that the prediction model overestimates the energy use and vice versa.

Units: kWh/m^2	Metered energy use	DD model		Hourly ML model (Random Forest)		Hourly ML model (Neural Network)	
Month		Prediction	Percentage error, %	Prediction	Percentage error, %	Prediction	Percentage error, %
Jan-22	10.81	8.9	17.5	9.02	16.6	9.2	14.5
Feb-22	8.13	7.5	8.2	7.52	7.6	8.2	−0.3
Mar-22	8.51	7.6	11.1	7.63	10.4	7.7	9.7
Apr-22	7.92	7.8	1.4	7.74	2.3	8.9	−11.8
May-22	8.71	8.8	−1.5	8.16	6.4	9.6	−10.7
Jun-22	9.27	9.9	−7.3	9.83	−6.1	10.7	−15.7
Jul-21	10.60	9.7	8.4	9.60	9.5	9.8	7.2
Aug-21	8.78	9.3	−6.2	9.79	−11.5	9.4	−6.6
Sep-21	9.48	11.4	−20.6	9.66	−1.9	9.9	−3.9
Oct-21	9.13	10.6	−16.2	10.11	−10.7	9.9	−8.9
Nov-21	9.56	9.7	−1.8	9.56	0.1	9.3	2.3
Dec-21	9.77	8.8	10.3	9.25	5.3	9.2	6.1
Total	**110.7**	**110.1**	**0.51**	**107.8**	**2.56**	**111.8**	**−1.02**
MAPE, %			**9.21**		**7.35**		**8.13**
R^2		−0.55		0.05		−0.04	
RMSE (kWh/m^2)		1.06		0.83		0.87	
NMBE		0.5 %		2.6 %		−1.0 %	
CV(RMSE)		**11.5 %**		**9.0 %**		**9.4 %**	

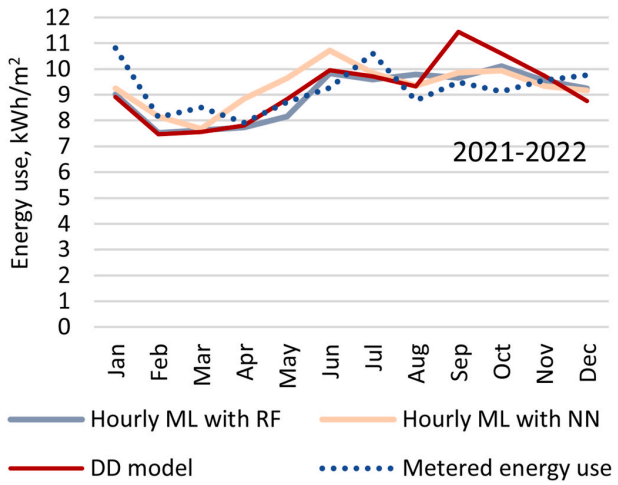


Fig. C.3. Metered electricity energy use compared with three different model prediction for 2021-07 to 2022-07 in RB1. The peak in September is due to high electricity use in base (last) year September.

Table C.4
Metered electricity energy use in kWh/m^2 compared with three different model prediction for period from July 2021 to July 2022 in RB2. The negative percentage error show, that the prediction model overestimates the energy use and vice versa.

Units: kWh/m^2	Metered energy use	DD model		Hourly ML model (Random Forest)		Hourly ML model (Neural Network)	
Month		Prediction	Percentage error, %	Prediction	Percentage error, %	Prediction	Percentage error, %
Jan-22	7.89	7.2	9.0	7.22	8.5	7.2	9.3
Feb-22	6.49	7.1	−10.0	7.03	−8.2	7.0	−8.2
Mar-22	7.53	8.4	−11.6	8.01	−6.4	8.1	−7.4
Apr-22	7.61	6.6	13.0	6.41	15.7	7.0	7.4
May-22	8.04	7.1	11.9	6.56	18.5	7.2	10.0
Jun-22	8.38	8.5	−1.9	8.54	−2.0	8.4	−0.7
Jul-21	10.05	9.5	5.6	9.52	5.3	8.8	12.7
Aug-21	8.83	8.1	8.1	8.46	4.3	7.8	11.2
Sep-21	7.64	8.0	−4.3	7.35	3.8	7.3	4.8
Oct-21	7.26	7.9	−8.5	7.67	−5.7	7.8	−7.3
Nov-21	6.78	7.2	−5.9	7.10	−4.8	6.9	−2.5
Dec-21	6.92	6.9	0.8	6.82	1.5	6.8	1.9
Total	**93.4**	**92.5**	**1.02**	90.7	**2.93**	90.4	**3.23**
MAPE, %			**7.55**		**7.06**		**6.95**
R^2		0.51		0.48		0.51	
RMSE (kWh/m^2)		0.65		0.67		0.66	
NMBE		1.0 %		2.9 %		3.2 %	
CV(RMSE)		**8.4 %**		**8.6 %**		**8.4 %**	

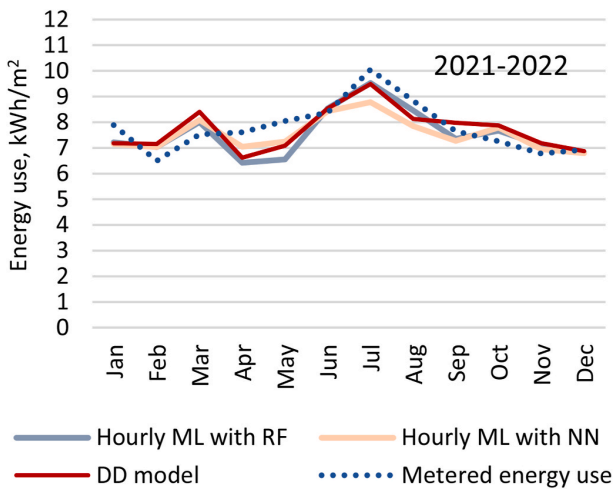
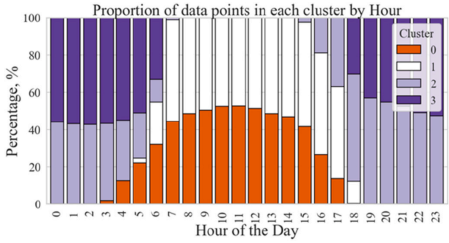
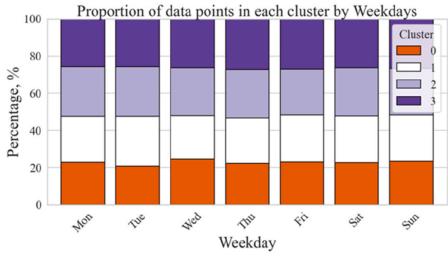
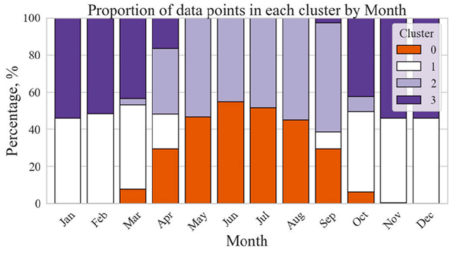
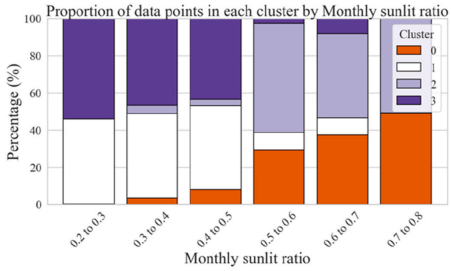


Fig. C.4. Metered electricity energy use compared with three different model prediction for 2021-07 to 2022-07 in RB2.

Appendix D

Table D 1
Identified clusters for heating energy use modelling

Visual description of clusters for heating energy use regression models training





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Table D 1 (*continued*)

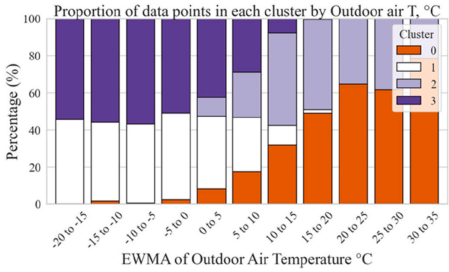
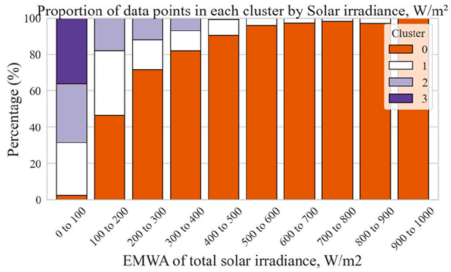
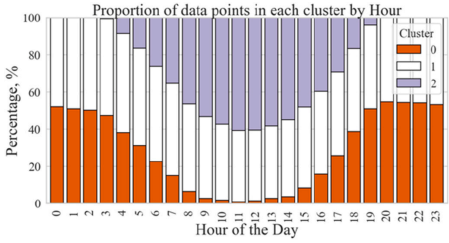
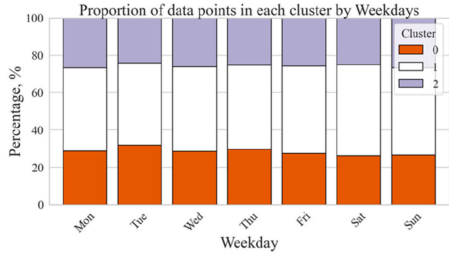
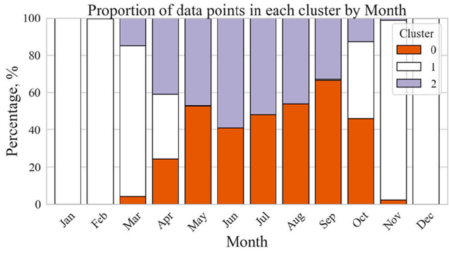
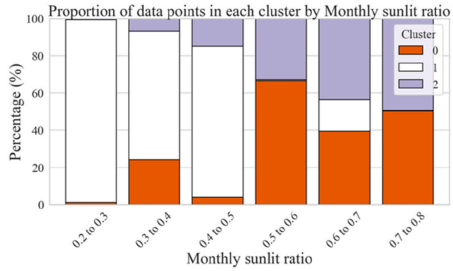
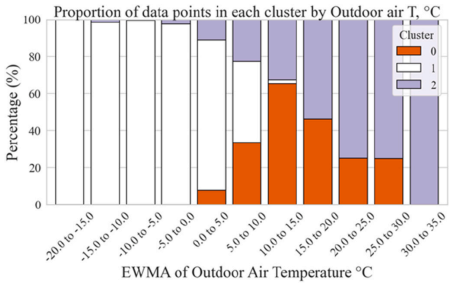
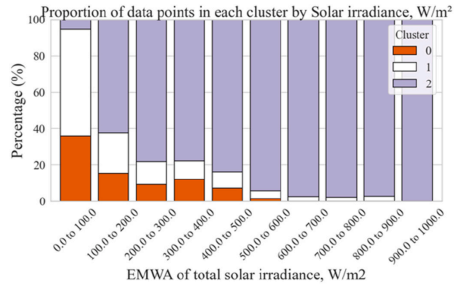
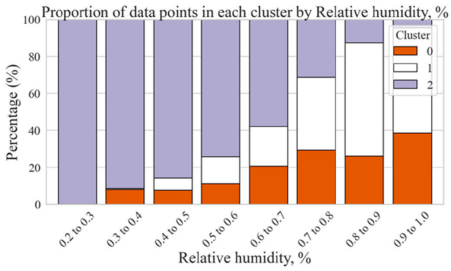
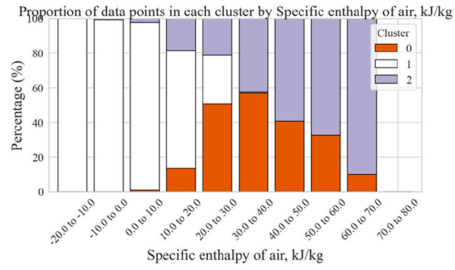
Visual description of clusters for heating energy use regression models training



Table D 2
Identified clusters for electricity energy use modelling.

Visual description of clusters for electricity energy use regression models training





(*continued on next page*)

Table D 2 (*continued*)

Visual description of clusters for electricity energy use regression models training





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Metered Energy Normalization in Non-residential Buildings for Compliance Assessment with EPBD Minimum Energy Performance Standards

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Abstract. The 2024 recast of the Energy Performance of Buildings Directive (EPBD) establishes new provisions for existing buildings as minimum energy performance standards (MEPS) for the worst performing non-residential buildings. One option to implement MEPS is to adjust energy performance certificate (EPC) scale so that class F and G will correspond to 26% and 16% worst performing buildings in the building stock. In such as case class G buildings must be renovated to at least class F from 2030 and class E from 2033. EPBD states that the EU Member States should develop a method that will consider the influence of the behaviour of occupants and the local climate if EPC is based on metered energy [1]. This study examined the user and systems operational hours impact on energy use in one office building. It aimed to develop a method for normalizing the energy use for extended hours. A calibrated simulation model was compiled to compare three cases: the building actual usage with non-standard operational hours, similar case with additional base load, and a standard usage case stated by Estonian regulations. The actual model's energy use differs about 8–10% and 16–25% from the standard model, respectively for heating and electricity energy use. The normalization method using hourly heating and electricity energy use, and actual and typical operational hours revealed to be reliable to conduct operational hours normalization with a few percent accuracy.

Keywords: heating and electricity energy use normalization · simulation model · operational hours adjustment

1 Introduction

European Union have been taken the goal to reduce its greenhouse gas emissions, and one solution is to reduce buildings energy use that is responsible of 40% of energy use in Europe. The Energy Performance of Buildings Directive (EPBD) introduces minimum energy performance standards (MEPS). In MEPS the energy performance certificate calculation process should consider the influence of the local climate and the behaviour

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of occupants [1]. Non-residential buildings often exceed their operational hours intended by standards that will impact the final EPC. Therefore, in this study, we focused on the normalization method considering operational hours of the building. Furthermore, we focused on simplified methods that are applicable on metered energy use as those may save the time and workload of energy performance assessment. There is lack of studies on energy use normalization methods that considers the operational hours while using metered energy use. We researched different national methodologies who are using metered energy use and apply operational hours adjustment. Ireland and USA are using adjusted benchmarks for longer occupancy hours [2, 3]. Sweden regulations allow adjustments of heating and cooling energy for buildings with unusual internal loads [4]. Other countries in European Union are mostly based on calculated energy use assuming standard use of the building or combined methods [5, 6]. In contrast, this study will focus on the methodology for normalizing the metered electricity and heating energy use comparable to standard energy use considering the difference of occupied and operational hours - operational hours adjustment.

2 Method

The study was based on energy simulation in IDA Indoor Climate and Energy 4.8 (IDA-ICE) software [7]. The output of the simulation models was used to validate the normalization method and identify the most accurate input for the operational hours' adjustment.

2.1 Reference Building and Simulation Models

The reference building (Fig. 1) built in 2009 is a 5-storey university facility at TalTech campus with a heated floor area 10 360 m^2. The total heat loss of the building envelope per heated floor area was 0.55 W/(m^2*K) and the WWR is 33% with window solar factor 0.4. Building has central heating system and water-cooled compressor chiller. Its simulation model with heated area 10 574 m^2 and calibration are detailed in Helena Kuivjõgi et al. study [8].



Fig. 1. Reference building in TalTech campus

Using calibrated model, we developed four models described in Table 1. To validate the developed method, the normalization of REAL model energy use was compared with STD model energy use. The error was described with mean absolute percentage error (MAPE) and Coefficient of Variation of the Root-Mean-Square Error (CV(RMSE)).

Table 1. The description of two REAL and two STD models compared

Model version	Description
REAL model	Reflects an office building with extended operational hours, incorporating the air handling unit (AHU), plugs, lights and occupancy profile.
REAL model + base load	using the equipment and lighting profile from [9] (without monthly differences), where the average base load is 2.7 W/m^2.
Standard (STD) model	Represents a standard office building defined in Estonian regulations [10, 11].
STD model + base load	Same as STD, but in outside operational hours, the power load is 2.7 W/m^2.

The plugs and lights load were defined only in workdays (no weekend usage), with identical maximum power loads. The profiles were defined so, that the average electrical power of the plugs and lights will be 8.25 W/m^2 during operational hours (Fig. 2). The main parameters of simulation models are shown in Table 2.

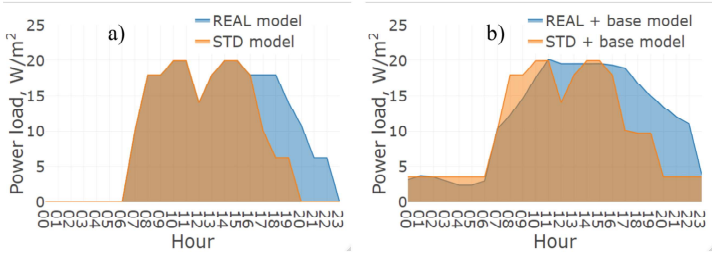


Fig. 2. Total electricity load of simulation models during the workday on February 6 for REAL model (a) and REAL+ base load model (b)

2.2 Operational Hours Adjustment

The operational hours adjustment was based on the building's operational hours and hourly energy use. The operational hours were defined by the "building owner" - the schedule defined in the simulation model. Two methods for defining the operational hours were tested: the user schedule, indicating when the building is occupied, and the

Table 2. Parameters of the simulation models

Average occupancy, no/m^2	0.077
Maximum appliances power, W/m^2	6.96
Maximum lighting power, W/m^2	8.96
Heating set-point, °C	21
Cooling set-point, °C	25
Air change rate, l/(s × m^2)	2.5
Compressor efficiency (SEER), –	3.5
AHU SFP kW/ (m^3/s)	2.1
AHU heat recovery efficiency η, %	40–75
DHW specific use, l/(m^2 × $y_)$	103

AHU schedule, indicating when the AHU is operating. Furthermore, the definition of partial and active use was tested. Partial use refers to when the building is partially occupied, or the AHU is operating at 50% capacity. The schedules for the operational hours are shown in Fig. 3 and calculated hours in Table 3.

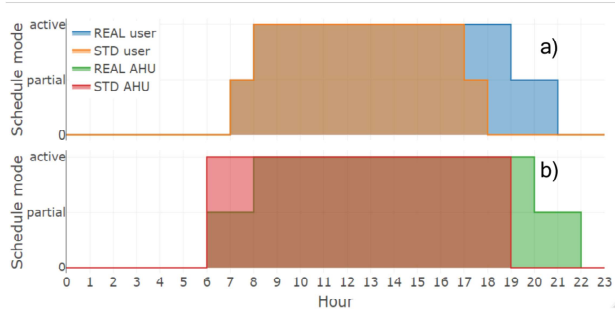


Fig. 3. Building occupancy (a) and AHU (b) operational hours schedule defined in simulation models using active and partial use

Monthly adjustments were made using hourly energy use data. Average power load during operational and non-operational hours were used to calculate normalized energy use by multiplying them with standard hours for each month (Fig. 4). The normalization was done using equation (Eq. 1), where the $E_{normalized}$ represents monthly normalized energy use (both, for electricity or heating), $t_{STD,op.}$ and $t_{STD,non.op}$ are standard operational and non-operational hours. The $\overline{P}_{REAL,op}$ and $\overline{P}_{REAL,non.op}$ are average power loads from REAL model data during operational and non-operational hours in specific

Table 3. Different versions of operational hours for REAL and STD models

Version		Operational hours	
		REAL/REAL+b.	STD/STD + b.
All operational hours	AHU	16	13
	User	14	11
Only active operational hours	AHU	12	13
	User	11	9

month. Reference building operational hours are detailed in Table 3.

$$E_{normalized} = t_{STD,op} * \overline{P}_{REAL,op} + t_{STD,non.op} * \overline{P}_{REAL,non.op} \quad (1)$$

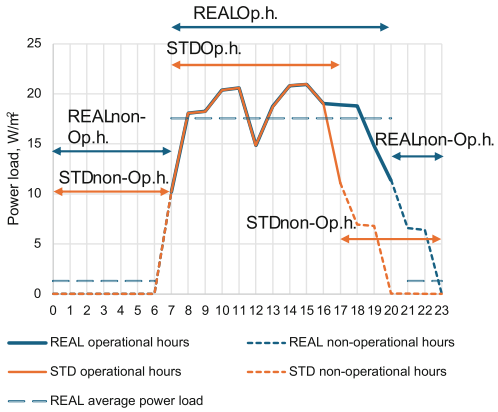


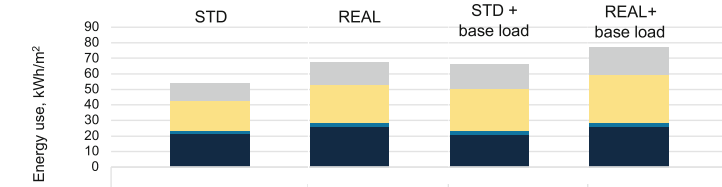
Fig. 4. The description of the method for operational hours adjustment. The REAL average power load will be calculated for operational and non-operational hours showed in figure and the STD hours for operational and non-operational hours were detected for the normalization.

The impact of operational hours adjustment was assessed by comparing total primary energy use. Heating energy use was first normalized based on operational hours adjustment and subsequently using the annual heating degree days (HDD) method. For the heating degree day method, the Space and AHU heating was divided with 2023 year HDDs and multiplied with the base year HDDs. The primary energy factor for heating energy is 0.65 (district heating) and for electricity energy 2.

3 Results and Discussion

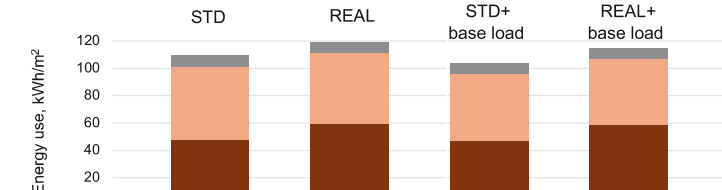
3.1 Energy Use of the Simulation Models (Before the Normalization)

The variation in annual electricity energy use (Fig. 5) among the models is greater than the variation in heating energy use (Fig. 6). Compared to STD model, the REAL model differs by 25% in electricity energy use, while the REAL+ base load (REAL+b.) model will differ 16% from STD + base model. Last mentioned comparison is less different due to the base load in non-operational hours.



	STD	REAL	STD + base load	REAL+ base load
Equipment	11.1	14.2	15.5	17.6
Lighting	19.3	24.6	26.9	30.4
Cooling	2.21	2.51	2.54	2.76
HVAC aux	21.2	26.1	21.2	26.1
Total electricity	53.9	67.4	66.2	76.9

Fig. 5. Models' energy balance for electricity energy use



	STD	REAL	STD+ base load	REAL+ base load
DHW heating	7.7	7.7	7.7	7.7
Space heating	53.6	52.0	48.2	48.0
AHU heating	48.1	59.3	47.6	58.8
Total heating	109.5	119.0	103.5	114.5

Fig. 6. Model energy balance for heating energy use

The heating energy use differences between models are minor (8% and 10%, respectively for without and with base load model). Compared to differences in electricity energy use, that does not vary much all over the year, for heating energy use the monthly percentage error varies between 4% to 15% for both versions.

3.2 Normalization of the Electricity Energy Use

Table 4 shows the MAPE and CV(RMSE) of the electricity energy use normalized with only active and all operational hours. The accuracy of normalizing REAL model energy use is below 10%. Only exception is with REAL model, where the results show, that using only active AHU operational hours, the normalization will not work (CV(RMSE) over 21%). Using all operational hours including partially occupied when the user is in the building (User in Table 4) would result minimum error with CV(RMSE) 1.3–1.5%.

Table 4. The MAPE and CV(RMSE) of normalized electricity energy use compared to STD model.

Version		MAPE, %		CV(RMSE), %	
		REAL	REAL+b.	REAL	REAL+b.
All operational hours	AHU	3.4	1.9	3.4	1.9
	User	1.5	1.2	1.	1.3%
Active operational hours	AHU	33	21	33	21
	User	10	7	10	7

3.3 Normalization of the Heating Energy Use

The heating energy use normalization has opposite results. The annual error is higher for result with base load than for without base load (Table 5). However, the results for active operational hours are lower than for electricity, still using all operational hours resulted lower error between 1% and 2.5% (CV(RMSE)). Going more detail, the monthly error varies between 0.3% and 7.4%. This is in the correlation with the monthly variations of initial case that is influenced by the solar radiation.

Table 5. The MAPE and CV(RMSE) of normalized heating energy use compared to STD model.

Version		MAPE, %		CV(RMSE), %	
		REAL	REAL+b.	REAL	REAL+b.
All operational hours	AHU	1.5	2.3	1.0	1.4
	User	1.6	2.5	1.1	1.6
Active operational hours	AHU	9	12	14	16
	User	5	7	6	7

3.4 Normalization Impact on Energy Performance Certificates

In Estonia, EPC for existing buildings is calculated from metered energy use. The EPC class limits of the primary energy use for office buildings are:

- E class below 261 kWh/m^2,
- D class below 210 kWh/m^2, and
- C class below 160 kWh/m^2.

The reference building simulation model's primary energy use was 221 kWh/m^2 and 237 kWh/m^2, respectively for REAL and REAL+ base load model (Fig. 7). This is assigned as EPC class E. The normalisation of heating and electricity energy use resulted with 189 kWh/m^2 and 210 kWh/m^2, respectively for REAL and REAL+ base load model. When using user operational hours, the result is very close to the model with standard profile, where the EPC-s are respectively 187 kWh/m^2 and 208 kWh/m^2. This means that operational hours' normalization moves the building with extended operational hours from EPC class E to D.

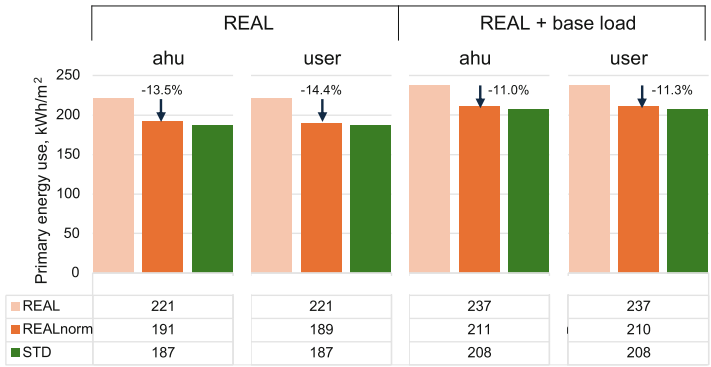


Fig. 7. The primary energy use of the normalization versions for two models

4 Discussion

The new EU regulations direct towards more accurate and comparable energy performance assessment methods within EU Member States. However, it has been realized that EPC ratings are not yet well comparable between Member States. One aspect is the difference in calculation methodology, and other is the ability to detect the occupancy and climate behaviour while assessing the energy performance of building. This study on simulation model shows that the simple operational hours adjustment method works with small error and could bring the real metered energy use more closer to standard building energy use. However, as in simulation model the building schedule was the same all over

the year, there is need to test this methodology on actual metered data from different type of buildings. In real cases, the building could have different operational times between months or even between weeks.

If we compare the REAL + base load model with STD model (without base load), that is usual case in the stock, the error becomes higher. Therefore, with metered data, the base load and other process energy that are not in EPBD scope should be omitted before the operational hours' adjustment.

The buildings operational hours is wide definition. It could be the opening hours, or the hours, when the user is in the building or when the AHU is operating, etc. Therefore, we tested the selection of the method for detecting the operational hours and as unified method, the result show that using the operational hours when the building is occupied works for both, electricity and heating energy use normalization. However, the buildings are different, and the final decision should be on the EPC assessor, who should choose the method that describes assessed building the best.

The heating energy use normalization resulted with small error. However, the monthly error varies in wider range. This is caused by the weather impact. In this study, the actual climate file was used, and the heating degree days normalization was done after the operational hours' adjustment. In further research, there should be tested the impact of the order of the normalization methods and how to neutralize the weather impact on other normalization methods.

5 Conclusion

The decarbonization of building stock needs more robust yet accurate energy use normalization methods for benchmarking. This study focused on developing a methodology for considering the influence of occupant behaviour on building energy use, with more detail on operational hours. The proposed operational hours adjustment would help provide quick and accurate feedback about building energy performance. It was found that in the reference office building, the most accurate is to obtain occupied hours (total operational hours when the user is in the building) from the building owner as input to normalize the metered energy use to standard energy use. However, this study outlined the problem with actual metered energy use that includes the base load outside operational hours, whereas standard energy use omits it. Therefore, its need for further research, how to use proposed methodology for normalizing metered energy use. Also, the heating energy use normalization method will need more research due to seasonal differences. Furthermore, this study is simulation-based and do not consider operational anomalies of metered energy use.

Acknowledgements. This work was supported by the Estonian Centre of Excellence in Energy Efficiency, ENER (grant TK230) funded by the Estonian Ministry of Education and Research, and by the European Union and Estonian Research Council via project TEM-TA78.

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PUBLICATION VI

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Metered energy normalisation methods for regulated energy use and operational hours in non-residential buildings

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Abstract

The revised Energy Performance of Buildings Directive (EPBD) introduces Minimum Energy Performance Standards (MEPS) for non-residential buildings, which thresholds can be two last categories of the energy performance certificate (EPC), intended to report energy used to condition indoor environment under typical use of the building. When EPCs are based on measured energy use, which may include energy uses not associated to conditioning of indoor environment (non-EPB uses) and deviations in operational hours from typical use exist, comparability with energy performance of building (EPB) scope may be lost. Therefore, to comply with MEPS thresholds, normalisation is required to separate energy use of EPB scope from main meter data and to adjust if operation deviates from typical use. This study proposes and validates two methods to normalize metered energy data. These methods address (i) non-EPB energy use by utilising monthly data of tenant electricity meters, and (ii) variations in operational hours based on hourly data of main meters. Application of tenant meters allowed to overcome a common problem that non-EPB energy use is often not measured separately. With this method remarkable reductions in primary energy, in some cases more than 50% are shown. The operational hours adjustment in a building with longer use, reduced primary energy by 14% and 10.1% for electricity and heating, respectively. Validation exercises conducted with detailed dynamic simulation models indicate that normalised results remained slightly conservative and made the performance gap visible if compared to the calculated EPC. Therefore, the proposed methods turned out to be robust and reliable both for non-EPB energy reduction and op-

erational hours adjustment. Application of these methods enables to use metered energy based EPCs to set MEPS requirements.

Keywords: MEPS, EPBD, energy performance assessment, commercial building, metered data, normalisation, simulation, performance gap

1. Introduction

1.1. Background

Since the Paris Agreement in 2015, the international goal has been to hold the increase in the global average temperature below 2°C above pre-industrial levels. [1] To achieve this goal, different schemes have been established worldwide. Building EPCs, together with green lease agreements, green bond financing, and pay-as-you-save models, play an essential role in achieving climate neutrality and energy efficiency targets. [2] Since 2007, the European Commission has adopted an Action Plan for energy consumption reduction. The 2024 revision of the EPBD now aims for a fully decarbonised building stock by 2050 [3, 4]. To achieve this goal, each Member State has to introduce MEPS for non-residential buildings in order to renovate at least 16 % of the worst-performing stock by 2030 and 26 % by 2033 (Figure 1). The worst performing buildings thresholds are based on EPC, which have been mandatory since 2002, when the European EPBD was published. EPC must be calculated when constructing, selling or renting a building. [5]

Current benchmarking system in the EPC. The EPC is the benchmarking and rating method, which relies on total primary energy use in kWh/m^{2}a as the standard indicator of building performance. According to the EPBD Annex I the calculation methodology of EPC should be based on calculated or metered energy use and shall reflect typical energy use of heating, cooling, ventilation, domestic hot water (DHW), lighting and other technical systems related to indoor environmental quality (IEQ). In other words, it includes services related to the EPB [6], while excluding non-EPB services, such as office equipment, catering, and computer rooms, which together account for roughly 47% of total energy use in U.S. commercial buildings. [7, 8, 9]

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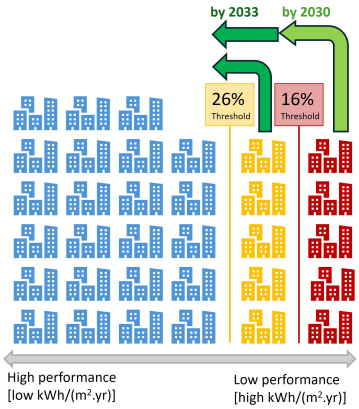


Figure 1: Non-residential buildings renovation plan - 16 % of worst-performing buildings renovated by 2030 and 26% by 2033 (adapted from [10])

Approximately 10 Member States in the EU derive their operational EPC using metered data, as this provides more reliable insights into building performance. Others use as-designed or as-built performance values to calculate building energy use. Using metered data is a quick and cost-effective market solution, which is particularly valuable in light of ambitious energy and climate targets. Moreover, metered data can serve as a benchmark for defining new energy-efficiency requirements for both new constructions and major renovations. However, the scope of EPBD is limited to energy that is used to condition the indoor environment under typical building use and user behaviour conditions. Therefore, operational ratings require further development through improved energy and occupancy monitoring, as well as the adoption of more robust calculation methodologies that enable the reflection of typical conditions and also minimize the cost of EPC calculation [11, 12, 13].

Energy performance assessment practices in other countries and regions. Similar to the European Union, other countries, such as the United States, Australia and South Korea, have established long-term strategies to reduce greenhouse gas (GHG) emissions by 2030 and 2050. [14, 15, 16, 17] Furthermore, the benchmarking of building energy performance is used worldwide to improve building energy efficiency and to support progress towards energy and climate targets. [18, 19] Since 1998, the Australian Commercial Buildings Disclosure (CBD) programme

has used the National Australian Built Environment Rating System (NABERS) Energy ratings. Today, it is mandatory for the sale or rental of commercial office spaces exceeding 1000 m^2. [20, 12] In the United States, the Energy Star certification has been a voluntary programme since 1996 that is used across multiple states. [21] This rating method is a peer group benchmarking system based on metered energy use. The peer groups are established based on building activity (e.g., office, hospital), using a nationally representative Commercial Buildings Energy Consumption Survey (CBECS) dataset, and the primary metric is Energy Use Intensity (EUI). In some states, the method is used to determine compliance with energy performance requirements. [22, 14, 23] In general, each country or union has established its own scheme for energy performance assessment, reflecting the historical context of regulations, building planning and construction practices. The main differences in assessment schemes in Europe are: 1) EPCs are mandatory; 2) benchmarks are determined based on typical building use rather than statistically derived from building datasets, and 3) EPCs may be based on calculated or metered energy use and must reflect typical conditions.

1.2. Problem statement

This study focuses on the impact of user-related factors on metered energy use in non-residential buildings, which strongly depends on the scale of the behavioural intervention. [24] Masoso et al. found that 56% of electricity was consumed during non-working hours, with base loads ranging from 8–18 W/m^2, primarily due to equipment such as computers and air conditioners left switched on [25]. Menezes et al. used Post Occupancy Evaluation[1] (POE) data to identify the building energy performance gap when comparing calculation in design-phase calculations with metered energy use. A model based on design parameters and standard occupancy hours accounted for only one-third of the actual energy use. They found that, over a typical week, the monitored occupancy profile indicated longer activity periods than the standard occupancy profile. When they incorporated sub-metered energy data and occupancy hours into the model, they achieved a difference of just 3% from actual energy use. [26] Furthermore, Kim et al. used electricity load data to predict hourly average electricity usage profiles for educational, office, retail, and cultural buildings. The results show that buildings of the same type may still exhibit very different hourly load profiles. Differences from standard profiles were also observed for some buildings within each category. [27]

[1] Post-Occupancy Evaluation (POE) is a structured process of evaluating the performance of a building after it has been built and occupied.

In conclusion, on the one hand, more accurate energy performance predictions requires more accurate inputs during the design phase and for asset ratings [28, 12], the integration of POE data [11], and comprehensive guidelines to support energy assessors [29]. Furthermore, the current benchmarking system should be improved to consider new practices in commercial buildings (e.g. review the typical use and base loads outside operating hours). [12, 30] On the other hand, the operational EPC based on metered data provides feedback on the building's actual performance and, when assessed properly, can reveal energy inefficiencies. [19] Therefore, there is need to ensure that assessments of operating buildings are more comparable with typical conditions. This is further complicated by limited data availability (e.g., lack of sub-metering) [19], highlighting the need for robust, large-scale data-driven methods for assessing building performance using metered data.

Therefore, this study focuses on two main questions:

1. How can energy used to condition the indoor environment during typical user behaviour be separated from metered energy data?
   a) If operation hours differ from the typical use, how can energy use be adjusted to correspond to typical conditions?
   b) How can tenant electricity meter data be utilised to complement main meter data?
2. How can fast and robust normalisation of metered data be conducted to correspond to the EPC scale, which is based on typical building use and energy used to condition the indoor environment?

1.3. Purpose of the research and novelty

Previous studies and national calculation methods have addressed the normalisation of domestic hot water (DHW), indoor temperature, and internal gains, typically using monthly metered energy use data. [31, 32] Furthermore, several studies have proposed methods to define benchmarks, predict the energy performance gap or energy consumption of commercial buildings using statistical and machine-learning algorithms using different input elements. [33, 34, 35, 23, 36] However, within the European EPBD framework, where the benchmarks are based on EPCs that assume typical conditions (weather and use), there is a lack of research supporting operational EPB assessment based on metered data for non-residential buildings with non-EPB energy uses or extended working hours.

This study introduces two previously unformalised normalisation procedures for assessing building energy performance using metered data, designed to improve the accuracy and comparability of EPCs. The first method developed in

this study enables adjustment for non-EPB energy use by using data from the main meter and tenants' electricity meters. The performance of the new method is demonstrated through case studies that report calculations based on monthly or annual system-level and tenant-level metered energy use data. This method enables the partial removal of non-EPB energy use, both by deducting energy from the main meter and by replacing with standard use data, thereby normalising the dataset to EPB services prior to performance evaluation. The second method adjusts for operational hours, accounting for variations in occupancy schedules between assessed buildings and reference conditions. By aligning energy data with standardised operational hours, this approach enables fairer comparisons across buildings with different usage patterns, including those with extended or reduced operating hours. The operational hours adjustment relies on hourly energy use data. Both methods were validated using simulation models.

2. Materials, data availability and regulatory context

2.1. Building stock and reference buildings

Wholesale and retail buildings comprising five supermarkets (Figure 2a and 2b) and two shopping centres (Figure2c) in Finland and Estonia were selected as reference buildings to exclude non-EPB energy use based on submetering and tenant meter (Table 1). All buildings are equipped with refrigeration systems for food storage and include several non-EPB uses such as external lighting, kitchen equipment, telecommunication rooms, elevators, and other auxiliary systems. The main air handling units are equipped with heat recovery, while restaurant kitchens use mechanical extract ventilation. Primary heat distribution consists of air heating or radiator systems, with fan convectors used at entrances and warehouse areas to prevent cold air infiltration. Office areas are additionally cooled by fan coil systems. District heating is the predominant heat source; however, supermarket SM1 uses a heat pump and SM4 heating is supplied by a local gas station.

The operational hours adjustment method was applied to normalise the energy use of the multi-purpose building (EDU1 in Table 1) with operational hours exceeding typical reference operating schedules. The five-storey university building (Figure 2d), located on the Tallinn University of Technology campus, was constructed in 2009 and has a heated floor area of 10 360 m^2. The building envelope heat loss is 0.55 W/(m^2*K), and the window-to-wall ratio (WWR) is 33% with a solar factor of 0.4. [37] The building includes classrooms, auditoriums, and offices. Air handling units are equipped with heat recovery, heating and cooling coils, while space heating is provided by a radiator system supplied by district

heating. In addition to EPB uses, the building also includes non-EPB energy uses such as servers, associated cooling systems, and outdoor lighting.



(a) The supermarket with floor area below 2500 m^2



(b) The supermarket with floor area 2500-5000 m^2



(c) The shopping center over 45 000 m^2



(d) The reference building in TalTech campus

Figure 2: Example of reference buildings

2.2. Metering infrastructure and data granularity

Energy use metering infrastructure varies between buildings. In Estonia, most buildings have whole-building metering, i.e., means main meters for utility energy use suh as heating, electricity, and gas, while submetering is less common. Depending on building function, sub-meters may be installed at tenant, system or equipment level. In multi-tenant buildings, tenant-level meters measure each tenant's energy use (appliances, lights and other tenant systems). In single-user buildings, system-level meters measure EBP and non-EPB services directly.

This study used energy data from main and sub-meters obtained from building owners, monitoring services, or building management systems (BMS). Selected buildings had at least annual tenant- or system-level submetering that included or directly measured non-EPB services. Most reference buildings used tenant-level metering with monthly readings (Table 1). One supermarket had annual system-level data, while two buildings provided hourly EPB and non-EPB system-level measurements.

Table 1: Summary of data availability and normalisation method in the selected reference buildings

Building ID	Building type	Meter	Data granularity	Metering infrastructure	Normalisation method
SC1-2	Shopping centre	Electricity and heating	Monthly	Tenant	Tenant meter
SM1	Supermarket	Electricity	Hourly	System	Submetering; simulation
SM2	Supermarket	Electricity and heating	Annual	System	Submetering
SM3-SM5	Supermarket	Electricity and heating	Monthly	Tenant	Tenant meter
EDU1	Multi-purpose building	Electricity and heating	Hourly	System	Submetering; operational hours; simulation

2.3. Data quality checks and pre-processing

In this study, the pre-processing procedure was determined by the need for adjustment, data granularity and the metering infrastructure (see Fig. 3):

- For annual or monthly system-level metered data, energy use data were organised according to the meter hierarchy prior to further adjustment.
- Annual or monthly tenant-level energy use data were categorised according to tenant usage type.
- Hourly tenant- or system-level cumulative metered data that did not require operational hours adjustment were aggregated to monthly values, after which the processing followed the same procedure as for monthly data.
- For hourly system-level metered data requiring operational hours adjustment, missing hourly values were identified and treated accordingly. In addition, the percentage of missing data per month was calculated in order to assess the sensitivity of the subsequent adjustment.

The university facility was equipped with hourly, system-level metering and required operational hours adjustment. Therefore, pre-processing was first conducted to enable energy use normalisation (see Fig. 3). Hourly cumulative energy

use data from the main meter and sub-meters were exported from the monitoring system. Hourly energy use was then calculated by subtracting the cumulative value of the previous hour from that of the current hour. Subsequently, the number and proportion of missing hourly records were determined for each month to evaluate data quality. The largest data gap occurred in December, with 74% of hourly values missing. January, June, July and November also exhibited significant data gaps, each exceeding 40% missing values. For further analysis, missing or faulty readings were filtered out from the main meter dataset. Missing readings in the sub-meter data were replaced with zeros to maintain consistency in the aggregation procedure.

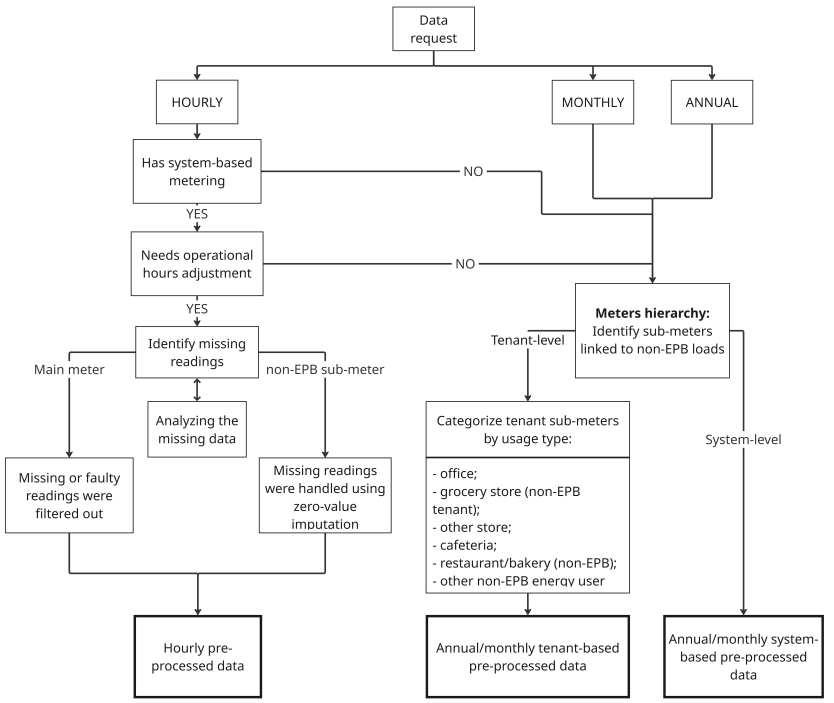


Figure 3: The decision tree and procedure for the pre-process of raw data from reference buildings

2.4. Regulatory constraints and Estonian EPC assessment framework

Focusing on the applicability within the European context, this study was based on the EPBD and the Estonian national regulatory framework, with particular emphasis on the EPC derived from metered energy use. In addition to the technical systems related to IEQ, the Estonian methodology accounts for energy use from appliances. All other services (non-EPB), like process energy, refrigeration, servers, catering, etc. should be excluded. However, EPBD do not prescribe how to exclude non-EPB services when not separately metered and how to adjust operational hours. Therefore, there is need for clear procedure for building energy performance assessment.

In Estonia, the standard operational hours are 8:00-16:00 for educational buildings, 7:00-18:00 for offices and 7:00-21:00 for wholesale buildings, with ventilation assumed to operate one hour before and after these periods. Outside the operational hours, the power loads of appliances and lighting remain zero. Standard electrical power densities in wholesale buildings are 15 W/m^2 for lighting and 1 W/m^2 for appliances.

In accordance with the Estonian national methodology [38, 39] the EPC was determined using Equation 1 and metered energy data for each building system and energy carrier. Space heating and ventilation heating were separated from total heating energy use to apply weather normalisation using heating degree-days (HDDs). After applying adjustments and weather normalisation, the energy use of each system was normalised to the heated floor area and aggregated. The total energy use was then multiplied by primary energy (PE) conversion factors 0.65, 1.0, and 2.0 for district heating, natural gas and electricity, respectively. In Estonia, the EPC benchmarks are fixed limits defined by building type. The operational EPC calculated by an assessor must be reproducible and is valid for up to ten years.

The following categories were considered as non-EPB services:

- Grocery store (refrigerated boxes, refrigerators, other non-EPB chillers, kitchen equipment, etc.)
- Restaurant (high power kitchen)
- Other special consumers (outdoor lighting, marketing screen, car wash, telecommunication room, elevator, server room electricity, chiller electricity, which serves, for example, a server, ice rink, or other systems unintended for HVAC)

$$E_{\mathrm{we}} = \sum_{j} \left(E_{\mathrm{we,adj,wnorm,H,cr},j} \cdot \mathrm{PE}_{\mathrm{cr}} \right) + \sum_{j} \left(E_{\mathrm{we,DHW,cr},j} \cdot \mathrm{PE}_{\mathrm{cr}} \right) + E_{\mathrm{we,adj,el}} \cdot \mathrm{PE}_{\mathrm{el}} \quad (1)$$

Where, E_{we} is EPC value as annual weighted specific use of delivered energy in kWh/m^2 per heated floor area, $E_{\mathrm{we,adj,wnorm,H,cr},j}$ is adjusted and weather normalised energy use for space and ventilation heating per energy carrier, $E_{\mathrm{we,DHW,cr},j}$ is energy use for domestic hot water per energy carrier, $E_{\mathrm{we,adj,el}}$ is adjusted electricity energy use, PE_{cr} is primary energy conversion factor per carrier.

3. Normalisation framework and methods

Under EPBD framework the EPC must reflect typical conditions in buildings. This study analyses user-related factors that needs to be considered while dealing with metered energy use. The focus is on non-residential buildings non-EPB energy use and variations in operational hours. The influence of base load outside operational hours was addressed with simulation model analysis. The additional aspects as deviations of indoor temperature and DHW use are not analysed, as they usually have smaller impact on total energy use in non-residential buildings. [40] These two aspects are also covered by the Swedish national normalisation method. [31, 32]

3.1. Overview of the normalisation workflow

After data pre-processing (Section 2.3), the EPC assessment procedure was followed with adjustment of non-EPB energy use with different method for hourly and monthly data. The operational hours adjustment continued by first defining the usage profile and thereafter conducting the normalisation. The flowchart of the full workflow for the energy performance assessment is in Appendix A.

3.2. Treatment of non-EPB energy use

The adjustment for non-EPB energy use (Figure 4) is a normalisation method developed for building energy use that excludes energy uses not considered in the scope of EPBD (hereafter referred to as non-EPB energy use). Non-EPB services were identified according to the classification defined in Section 2.4. Depending on the metering infrastructure described in Section 2.3, two following alternative procedures are defined. In both cases, the result is a monthly or annual total energy use value excluding non-EPB energy use, from which the final corrected EPC is calculated. Hourly energy use data must be adjusted on an hourly basis using system level data in order to enable subsequent operational hours' adjustment.

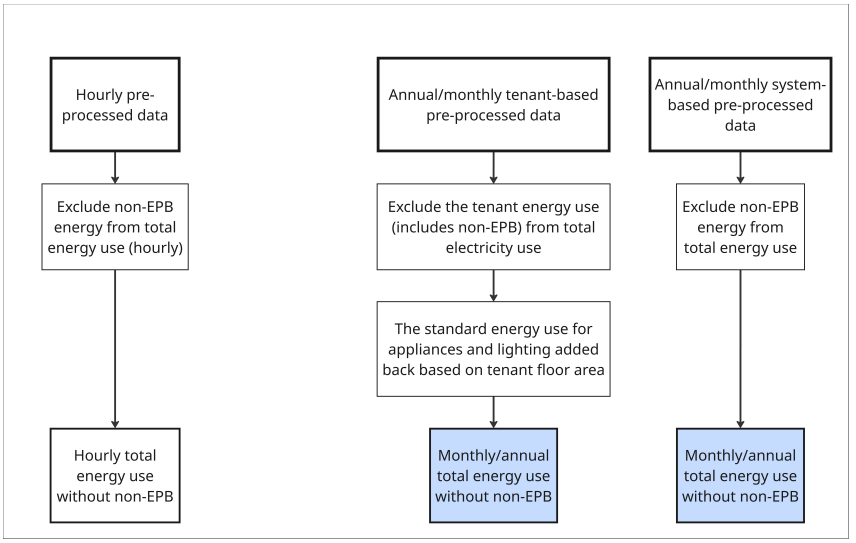


Figure 4: Flowchart describing the adjustment for non-EPB energy use

3.2.1. System-level metering case

In buildings where non-EPB services are measured through dedicated system-level sub-meters, the treatment of non-EPB energy use can be implemented through direct exclusion. The main meter provides total delivered energy, while individual sub-meters quantify the consumption of specific technical systems. Where such systems fall outside the EPBD definition of energy performance of buildings (e.g., refrigeration units, server rooms, catering equipment), their measured energy use can be subtracted from the total delivered energy prior to EPC calculation using Equation 2. This approach is applicable only when non-EPB services are metered independently and when interdependencies between systems (e.g., recovery of waste heat for space heating) are properly accounted for to avoid underestimation of EPB-related energy use.

$$E_{\text{adj,el}} = E_{\text{main}} - \sum_{i} E_{\text{non-EPB},i} \tag{2}$$

$$E_{\text{adj,el}} = E_{\text{main}} - \sum_{i} E_{\text{non-EPB},i} - \sum_{j} E_{\text{tenant},j} + \sum_{j} E_{\text{tenant,STD},j} \tag{3}$$

Where $E_{\text{adj,el}}$ represents energy use where non-EPB energy is excluded; E_{main} is total energy use from main meter; $E_{\text{non-EPB},i}$ is measured system that belongs to non-EPB service; E_{tenant} is tenant electricity that includes non-EPB energy, metered with meter j; $E_{\text{tenant,STD},j}$ is tenant appliances and lighting electricity energy use according to the building type from standard (Table 2). The unit for energy is kWh/a or kWh/m^{2}a heated floor area.

3.2.2. Tenant-level metering case

Where non-EPB services are embedded within tenant-level electricity measurements, direct subtraction of the entire tenant meter would remove not only process-related loads but also electricity uses consistent with typical EPB assumptions (e.g., appliances and lighting). This would lead to an underestimation of EPB-related energy use.

To address this limitation, a replacement-based normalisation procedure was applied. The measured tenant electricity was first excluded from the main meter total, after which standardised appliances and lighting energy values (Table 2), defined in the national EPC methodology [38], were reintroduced based on the tenant floor area. The adjustment was done with Equation 3.

3.2.3. Applicability and limitations

The adjustment for non-EPB energy use is applicable if at least the annual electricity energy use from main meter and non-EPB-associated tenant meter is available.

For tenant-level approach, it was assumed that all remaining energy, not attributable to non-EPB purposes, corresponded to appliances and lighting. Therefore, the tenant-level normalisation methodology is applicable only if there are no other technical systems intended to ensure indoor climate conditions (e.g., heat pumps or ventilation systems) connected behind the tenant's meter in addition to non-EPB energy, appliances, and lighting. Otherwise, the reduced energy use would no longer reflect the building's typical energy performance, as significant energy consumers would have been excluded.

3.3. Operational hours adjustment

In non-residential buildings, actual operational hours may differ from typical hours defined in standards (see Section 2.4), resulting in deviations from the reference conditions specified by the EPBD. To evaluate building energy performance under typical conditions while accounting for such variations, an operational hours adjustment method was introduced. This method provides as a

Table 2: Standard annual energy use for appliances and lighting from Estonian calculation methodology [38] by building type

Building type	Annual energy use, kWh/m^{2}a
Office	31.5
Wholesale and retail trade service building	45.0
Educational building	15.4

normalisation approach for comparing the energy use of buildings with different usage patterns, including those operating beyond or below typical hours.

Following data pre-processing (Section 2.3) and the adjustment of non-EPB electricity use (Section 3.2), the operational hours adjustment procedure (Figure 5) was applied to normalise the energy use of the multi-purpose building with extended operational hours. The procedure comprises three steps: identification of operational and non-operational hours, calculation of the corresponding power or heat load within these periods, and normalisation to the standard operational hours defined by regulation.

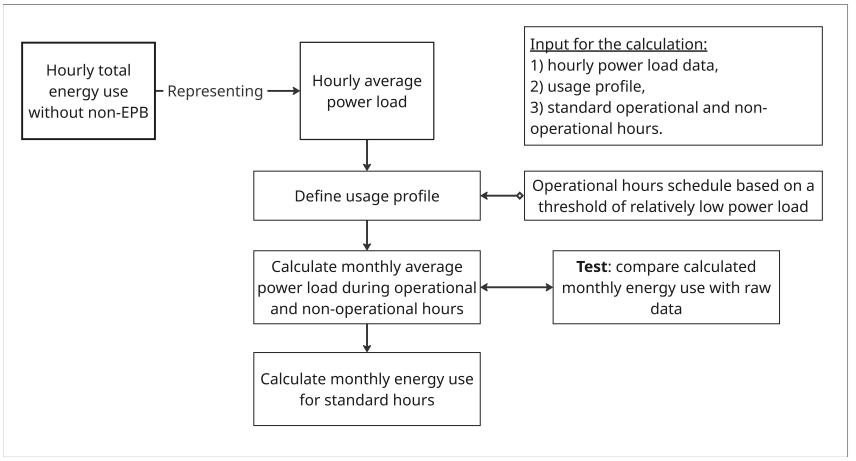


Figure 5: Flowchart describing the operational hours adjustment

3.3.1. *Identification of operational and non-operational hours*

Detection of operational hours is necessary because calculated EPC rely on fixed schedules that often differ from actual building use. Actual operational hours are typically identified by information provided by the building owner or manager. However, in non-residential buildings, occupancy profiles have been shown to correlate strongly with lighting, appliances or total electricity demand and can therefore be inferred from hourly electricity data. [41, 26, 42, 43, 44, 45, 46, 36] Caution is required in multi-purpose buildings or during seasonal breaks, where occupancy and energy use may decouple. [42, 34]

In this study, a user profile was derived by analysing daily power-load patterns, occupancy data, such as classroom bookings and office rooms access log, and defining a baseline threshold separating operational from non-operational periods (Figure 6). The hourly electricity use data was expressed as average power load, assuming that the actual power load remained constant within each hour. Because the reference building operates under different weekday and weekend schedules, separate annual profiles were established for weekdays, Saturdays, and Sundays.

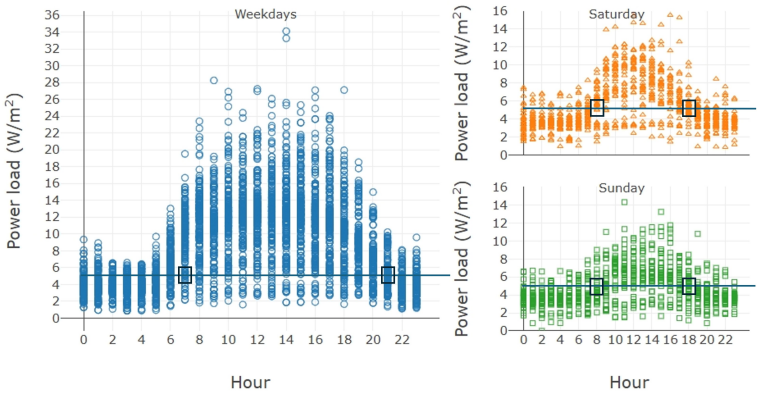


Figure 6: The daily power load as usage pattern for weekdays, Saturday and Sunday

3.3.2. *Normalisation process*

After user profile was defined, it was used to calculate average power or heat load for each month operational and non-operational hours (example in Figure 7, where $P_{\mathrm{op},i}$ represents average load in month i during operational hours (W/m^2); $P_{\mathrm{non.op},i}$ is average load in month i during non-operational hours (W/m^2). Figure 7

also shows that outside the operational hours, the electrical power load is around 4-5 W/m^2 and that is defined as base load. In standard calculations, the non-residential building base load is near zero as the appliances and lighting do not work outside operational hours.

Using the calculated power loads and standard hours, the adjusted annual energy use was calculated with Equation 4. The t_d is building operational hours per day according to Estonian regulations (hours); t_w is building operational days per week according to Estonian regulations (days); t_i total hours in month i (hours).

Reference building serves multiple functions, with 43.8% of the floor area allocated to office and 56.2% to educational space. To account for the mixed-use composition of the building, the monthly load was first apportioned according to the floor area assigned to each functional use. The normalisation was then carried out separately for each use by applying the corresponding specific load and standard operational hours. Finally, the normalised energy values for each use were then aggregated to determine the total normalised energy use of the building.

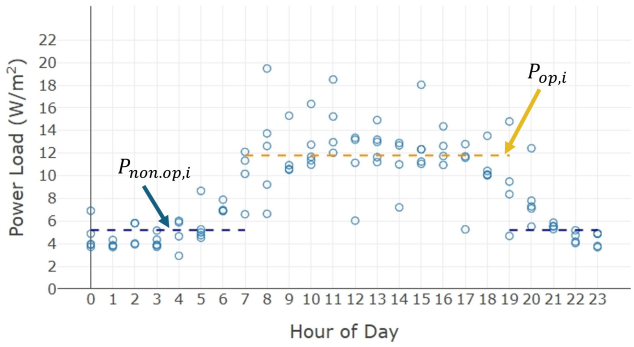


Figure 7: Daily pattern describing the operational hours adjustment for weekday in April

The power load and usage profile derivation was tested by comparing the calculated energy use (using Equation 4 with actual operational hours) with metered data that was reduced by non-EPB energy use (method described in Section 3.2). The raw monthly energy use was calculated from cumulative values by subtracting the last available hourly value of the previous month from the last available hourly value of the current month, except for January, where the first available hourly value of the current month was subtracted from the last available hourly value.

$$E_{\text{adj}} = \sum_{i=1}^{12} \left(P_{\text{op},i} \frac{\tau_d}{24} \frac{\tau_w}{7} \frac{t_i}{1000} \right) + \sum_{i=1}^{12} \left(P_{\text{non.op},i} \left(1 - \frac{\tau_d}{24} \frac{\tau_w}{7} \right) \frac{t_i}{1000} \right) \quad (4)$$

3.3.3. Applicability and limitations

This approach requires hourly data for calculating monthly average power load and is therefore not applicable with only monthly or annual data. Furthermore, the user profile detection should be coordinated with information provided by the building owner or during observation.

4. Application to case study buildings

Following section will give the overview of the application of two methods and the validation procedure. The comparison and validation metric was Coefficient of Variation of the Root-Mean-Square Error (CV(RMSE) (Equation 5), as recommended by ASHRAE Guideline 14-2023 [47].

$$\text{CV(RMSE)} = \frac{\sqrt{\frac{\sum_{i=1}^{n} \left(Y_i - \hat{Y}_i \right)^2}{n - p}}}{\bar{Y}} \times 100 \quad (5)$$

Where, Y_{i} represents monthly metered energy use (kWh/m^2), $\hat{Y}_i$ represents monthly predicted energy use at the same time (kWh/m^2), $\bar{Y}$ is the mean of the metered energy use over the period (annual) (kWh/m^2), n is the number of data rows (months), and p is the number of parameters or terms in the baseline model, considered as 2 for the prediction models in this study.

4.1. Application of non-EPB adjustment to retail buildings

4.1.1. Supermarket 1

The following electricity sub-meters were installed in the supermarket used to validate the methodology, providing an overview of the building's actual energy balance (Figure 8):

- Refrigeration chillers
- Facility electricity
- Other non-EPB energy use

- Tenant (appliances and lighting)
- Heat pump using waste heat from refrigeration

In this case, it was particularly important that the heat pump, which heats the building using waste heat from the refrigeration, was measured with a separate meter and therefore not excluded during the adjustment.

The EPC based on the main meters was 490 kWh/m², corresponding to energy class G. After applying the adjustment using system-level meters, electricity energy use was reduced by 55% (Figure 9). The corrected EPC was 221 kWh/m^2, which corresponds to energy class D. Tenant-based approach was tested using two values: (i) total metered energy use, and (ii) the grocery store's energy use (including refrigeration, appliances, and lighting). This resulted in a corrected EPC of 226 kWh/m^2, representing a 54% reduction (Figure 10). The result is 5 kWh/m^2 greater, because the other non-EPB energy use was not excluded.

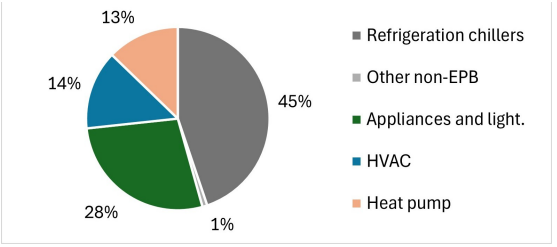


Figure 8: The electricity energy balance for Supermarket 1

4.1.2. Supermarket 2

In SM2 having a calculated EPC rating of 149 kWh/m^2, corresponding to class A, the following energy meters were installed:

- Main electricity meter (energy balance in Figure 11)
  - Sub-meters: general electricity, storage, lighting, tenant, appliances, refrigeration, kitchen ovens, electric vehicle charger, outdoor lighting
- Main heating energy meter

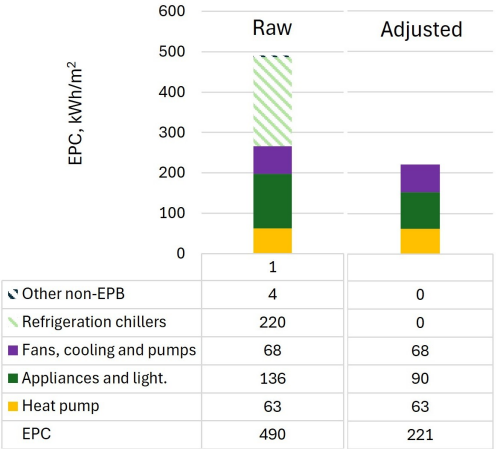


Figure 9: Supermarket 1 primary energy balance with system-level metered energy use (left) and adjusted, without non-EPB energy (right)

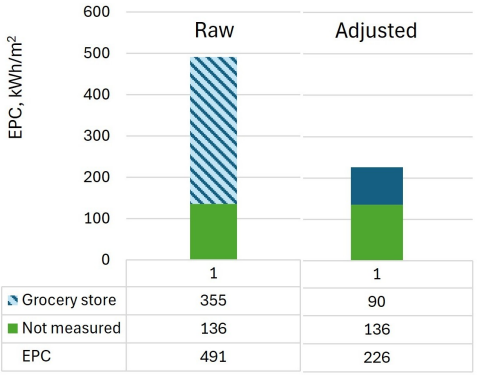


Figure 10: Supermarket 1 primary energy balance with tenant-level metered energy use (left) and adjusted, without non-EPB energy (right)

Based on the measured data, it was possible to subtract the non-EPB energy and apply a corresponding correction to the EPC. The adjustment led to a 56% reduction in the primary electricity energy use, bringing the EPC from class G (533 kWh/m^2) to class E (233 kWh/m^2) (Figure 12). The share of non-EPB energy was 43% and 7.2% in the EPC, respectively, for non-EPB services and appliances.

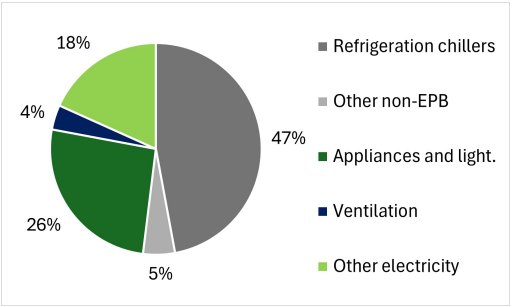


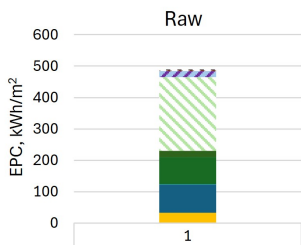
Figure 11: The electricity energy balance for Supermarket 2

4.1.3. Supermarket 3

In supermarket 3, the following electricity meters were installed:

- Main electricity meter
- Sub-meters: grocery store (tenant), tenants' plugs and lights, restaurant (tenant, high power kitchen)
- Main heating energy meter

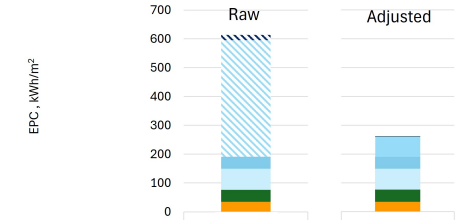
The calculated EPC in supermarket 3 was 205 kWh/m^2, corresponding to class C. In this building, non-EPB energy was not metered separately; however, the tenants' electricity energy use, which includes non-EPB energy, was measured. Applying a tenant-level methodology improved the EPC from class G to class B (148 kWh/m^2), representing a 76% reduction in primary energy use. In the case of Supermarket 3, waste heat from refrigeration units is also used for heating, but this is not separately measured. Furthermore, "Grocery store" category include other end-uses that do not fall under appliances and lighting but still is considered as typical use (e.g., ventilation, cooling, water heater). In such cases, it is essential that the EPC assessor identifies which loads fall under subtractable non-EPB



	1	1
non-EPBD lighting	2.0	0
Electric charger	3.4	0
Bakery oven	19	0
Refrigeration	236	0
Appliances	0	6
Ventilation	19	19
Lighting	86	84
Tenant electricity	2.0	2.0
Warehouse + Eq+light	0	0
Property	89	89
Heating	33	33
EPC	490	233

Figure 12: Supermarket 2 primary energy balance based on metered data (left) and without non-EPB energy (right)

energy and ensures they are properly accounted for in the EPC calculation. This can be achieved, for example, by measuring average power with a clamp meter and incorporating the operating time of the technical system in the calculation. In this study, such measurements were not conducted. However, to give an example, proportions for HVAC (14%) and Property (8%) were taken from previous case studies to estimate their share of energy use within the "Grocery store" category. The corrected EPC was 262 kWh/m^2, representing a 57% reduction (Figure 13). This result is similar with findings from previous case studies, and more realistic compared to the calculated EPC.



	Raw	Adjusted
Restaurant	18.8	1.4
Grocery store	404.5	69.8
Grocery store: Property	41.5	41.5
Grocery store: HVAC	72.6	72.6
EPBD electricity + Equipment	42.5	42.5
Heating	34.3	34.3
EPC	614.3	262.2

Figure 13: Supermarket 3 primary energy use metered (left) and without non-EPB energy (right)

4.1.4. Summary of the results from wholesale and retail buildings

In all buildings, it was possible to reduce the electricity energy use not considered in the EPBD (marked grey in Figure 14). The reduction was approximately 50%. However, in the case of buildings SM3 and SM5, a more detailed investigation and calculation were required to ensure that no technical systems intended for maintaining indoor climate remain mistakenly classified as non-EPB energy.

4.1.5. Multi-purpose building

The multi-purpose building required operational hours adjustment, therefore, the adjustment for non-EPB energy use was performed on an hourly basis by subtracting the sum of non-EPB energy use from the total energy use. The initial EPC calculated from metered energy use was 275 kWh/m^2, which belonged to

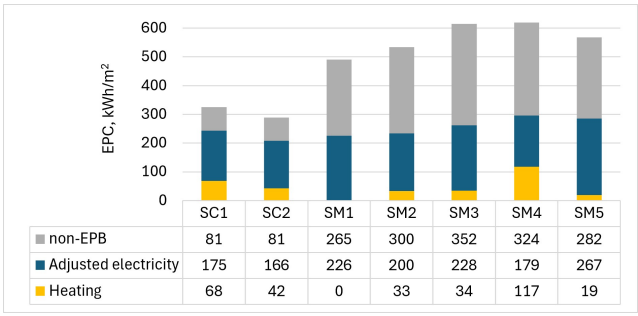


Figure 14: Wholesale and retail buildings EPB and non-EPB primary energy use

class F. After the adjustment, the EPC was 196 kWh/m^2, and the class was D. (Figure 15)

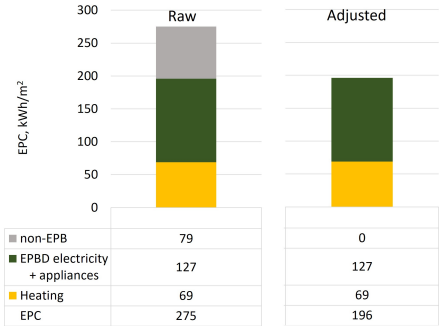
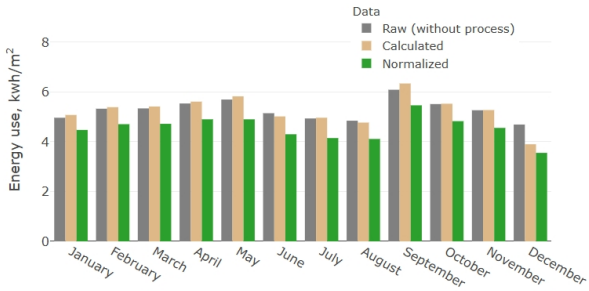


Figure 15: Primary energy use metered (left) and without non-EPB energy (right) of the university facility

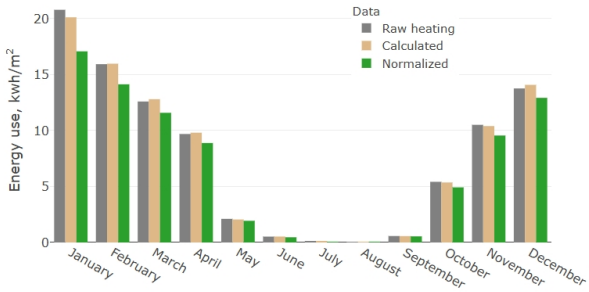
4.2. Application of operational hours normalisation to a multi-purpose building

The calculated monthly total energy use was compared with metered data. The CV(RMSE) was 5.21% and 3.26%, respectively, for electricity and heating energy use (raw and calculated in Figure 16). Furthermore, the primary energy use was similar across the raw, calculated, and calibrated simulation model results (190-191 kWh/m^2 in Figure 17 and 22).

The normalised energy use CV(RMSE) compared to raw data was 15.35% and 18.71%, respectively, for electricity and heating energy use (Figure 16). The



(a) Electricity energy use



(b) Heating energy use

Figure 16: The initial monthly energy use compared with calculated and normalised energy use

normalisation resulted in a reduction of the primary energy use for electricity by 17.3 kWh/m^2 (14%), and heating by 6.4 kWh/m^2 (10.1%) (Figure 17)

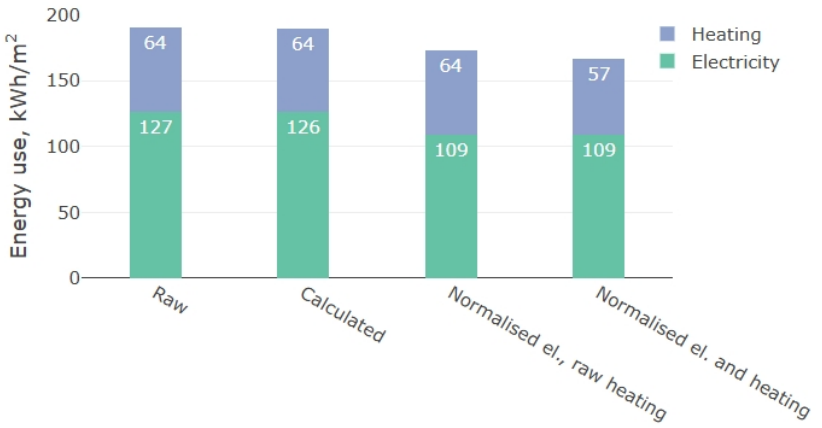


Figure 17: The primary energy use comparison between different calculations

The weather normalised energy use was the final EPC. The correlation factor was 1.08, and therefore the heating energy use increased by 8%. The EPC calculated with raw energy use was 196 kWh/m^2 (Figure 18). The normalisation reduced the EPC by 12.8% to 171 kWh/m^2. The EPC class stayed at D, but the reduction was remarkable and would be more comparable to other similar buildings.

5. Validation

The energy simulation models were used to validate the normalisation procedures. The adjustment method for non-EPB energy use was compared with standard based simulation model for one representative supermarket (SM1). The validation of the operational hours' adjustment was conducted using a calibrated simulation model of multi-purpose building (EDU1) in university campus (Figure 2d; detailed more in Section 2.1).

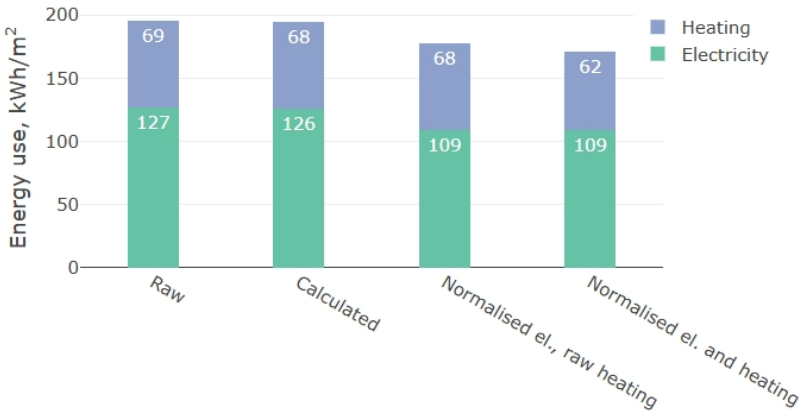


Figure 18: The primary energy use with weather normalisation (EPC) comparison between different calculations

5.1. Supermarket SM1 simulation model

The simulation model (Figure 19) was created using IDA Indoor Climate and Energy software 5.1 [48]. The model was based on the building design documentation, technical specifications and control strategies of the air handling units (AHUs), information on the installed systems, and in-situ observations. The weather file in simulation model was ASHRAE IWEC2 Weather File for Jyväskylä, Finland. The main parameters in the simulation model are outlined in Table 3.

The indoor climate of the building is maintained by two air handling units (AHUs). The sales area, which represents 40% of the total floor area, is conditioned by an AHU equipped with heating and cooling coils. A second AHU serves the staff and utility rooms, accounting for 41% of the total floor area, where space heating is mainly provided by radiators. Food storage rooms (5% of the total floor area) are cooled by refrigeration equipment and ventilated by a mechanical extract ventilation system without heat recovery.

Lighting and appliance power densities in the simulation model follow the Estonian national methodology [38, 39], ensuring consistency of internal heat gains with the national calculation framework.

The actual building is equipped with a heat recovery heat pump that recovers heat from the refrigeration system and supplies heat for space heating, AHU heat-

ing and domestic hot water (DHW). The district heating is as back-up solution. This heat recovery system was not explicitly modelled in the simulation model. Instead, the heat demand was calculated and the corresponding electricity consumption was estimated using conservative value of coefficient of performance (COP) listed in Table 3.

Another difference between the actual building and the simulation model concerns humidity control. The real building includes a dehumidification system that operates during summer conditions, whereas no dehumidification was implemented in the simulation model. Furthermore, the heat loss due to refrigeration equipment in sales area and food storage room was not included in the model, in order to represent typical indoor thermal conditions. Accordingly, the total floor area was reduced by 143 m^2, representing the food storage room, where the temperature is significantly below typical conditions.

Regarding HVAC energy use, the simulation model considers only heating, cooling, AHU fan electricity and a default value of 0.5 kWh/m^2 per year for heating circulation pumps. Electricity use of auxiliary equipment for the heating and cooling systems was not considered because reliable data for the actual building was not available. Consequently, the simulation represents an as-built standard model, excluding non-EPB energy use and dehumidification.

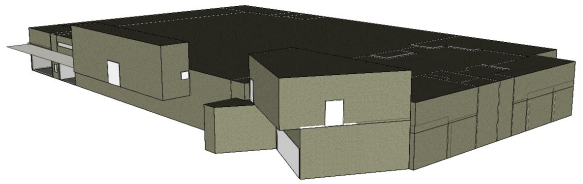


Figure 19: Simulation model of the supermarket SM1

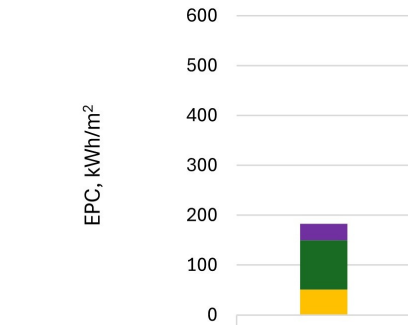
5.1.1. SM1 standard model results

An EPC calculated with energy use from supermarket simulation model was 182 kWh/m^2, which corresponds to class C (Figure 20.). This is a benchmark for the operational EPC, as it considers the reference building's energy use for systems related to IEQ under standard conditions. Comparing it with corrected

Table 3: Energy model input parameters

Parameter	Value
Internal gains	
Average occupancy, no/m^2	0.035
Maximum appliance power, W/m^2	1
Maximum lighting power, W/m^2	8.0
Thermal zones	
Floor area with air heating, m^2	1190
Floor area with radiators, m^2	1204
Heating set-point temperature, °C	
Grocery and connected sales area	18–22
Back space	18–25
Offices, rest rooms, WC	21–25
Ventilation	
Average air change rate, L/(s·m^2)	2.0
SFP for AHU, kW/(m^3/s)	1.8
SFP for exhaust fan, kW/(m^3/s)	0.67
AHU heat recovery effectiveness, %	55–70
HVAC system performance	
AHU cooling chiller efficiency (SEER)	3
Heat pump COP (space and AHU heating)	2.7
Heat pump COP (DHW heating)	2.1
DHW specific use, kWh/(m^2·a)	4.0

EPC, the difference is 44 kWh/m^2 (19%). Therefore, the adjustment for non-EPB energy use remains conservative, because actual metered energy use also includes heat loss due to refrigeration equipment, dehumidification and different auxiliary systems that are not always considered in energy performance assessment.

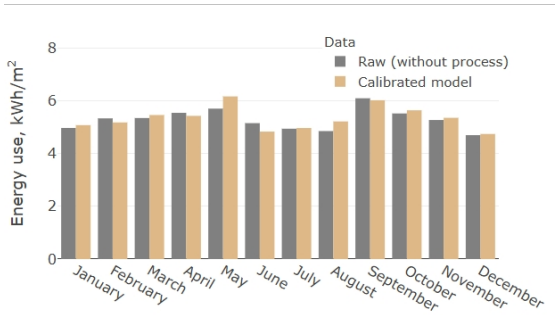


Other non-EPB	0
Refrigeration chillers	0
Fans, cooling and pumps	32
Appliances and light.	99
Heat pump	51
EPC	182

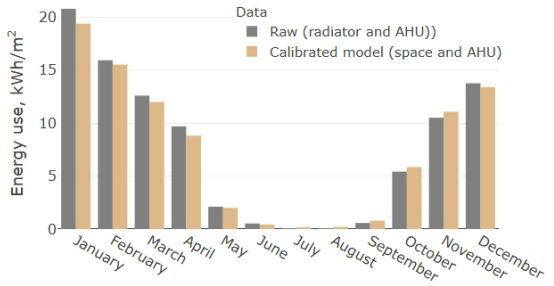
Figure 20: Energy balance of the simulation model of the supermarket SM1

5.2. Multi-purpose building EDU1 simulation model

The simulation model was developed in IDA Indoor Climate and Energy 4.8 (IDA-ICE) software [48], based on building documentation and in-situ observations. The simulation model was calibrated against metered energy use (Figure 21). The CV(RMSE) was 4.09% for electricity and 9.35% for heating energy use. The calibration achieved the ASHRAE threshold of less than 15% for computer model validation. Furthermore, the standard (STD) simulation model was derived from calibrated model where the lighting schedules and appliances power load and schedules were set according to standard values of educational and office building (standard profile excludes the base load). The outputs of the simulation models were used to compare the results and validate the operational hours adjustment method applied to the metered data.



(a) Electricity energy use



(b) Heating energy use

Figure 21: Calibration results of the of the university facility's simulation model

5.2.1. EDU1 standard model results

The EPC of calibrated model was 195 kWh/m^2, while that of the standard simulation model was 167 kWh/m^2 (Figure 22). The energy use under standard conditions is about 2.4% lower than the energy use normalised with operational hours adjustment. This reflects that the normalisation was slightly conservative, as it also includes the base load. Furthermore, comparing to the normalised value, the standard model's electricity use was 14.3% lower, which affected the heating energy use, making it 15.8% higher.

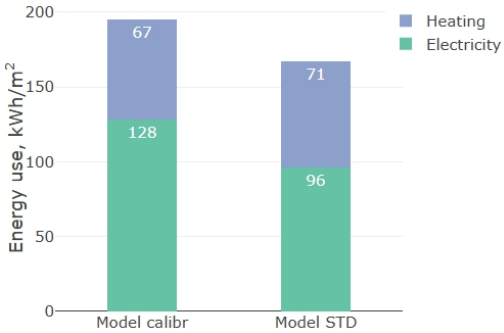


Figure 22: The primary energy use comparison between calibrated and standard (STD) simulation models

6. Discussion

Around the 1990s, the energy performance gap was identified when comparing measured energy use with energy simulation models [49]. The performance gap occurs when the calculated rating or predicted value differs significantly from the measured data. Today, building construction requirements for energy efficiency are more realistic. However, the gap may still persist. Previous studies have proposed various methodologies to reduce the performance gap, mostly focusing on residential buildings. Berggren et al. showed that normalisation accounting for differences in DHW, indoor temperature, and internal loads can reduce the performance gap by nearly 5% in residential buildings. [31] This study focuses on commercial buildings, where behavioural factors differ from those in residential buildings: for example, occupants have less control over indoor temperature,

DHW use is lower, non- IEQ related energy uses are more prominent, and buildings typically operate within specific time frames rather than continuously.

This study demonstrates that normalisation methods can be used to estimate regulated energy use and also to quantify the performance gap if energy calculation methodology is available. The proposed normalisation methods therefore estimate the energy required to condition the indoor environment under typical usage and operational hours, while still reflecting existing performance gap. This normalised energy use enables to compare EPB scope of similar buildings and serves as relevant value for metered energy based EPCs.

The application of non-EPB adjustment method reduced the share of non-EPB energy use in grocery stores by more than 50% (primary energy). Comparing with the energy use of supermarket standard simulation model, the result remain 19% higher. The impact of extended operating hours in office and educational building reduced energy use approximately 12%. A previous study using a simulation model reported reductions of 11%-14.4% [50]. If the operational hours adjustment was applied to metered data, the difference compared with a typical-use simulation model was 2.4%. The results show that the normalisation is somewhat conservative — as it should be — since it is preferable to report higher energy use than to risk underestimation. The truth may lie between the two, and normalisation based on measured energy use is always preferable, as certain simplifications are inevitably made both in the input data and in the calculations of the simulation model.

Lack of metering infrastructure. The aim of this study was to develop methods that are as simple as possible and require a minimum number of input parameters from building energy meters and stakeholders. The rationale for this is the current low quality of available data. Mahdavi et al. reviewed studies worldwide and found that the most common sources of energy data were bills (electricity, gas consumption) and data from principal meters, with sub-meters used only occasionally. Few studies (7%) employed dedicated energy use metering. [11] From an Estonian perspective, only a limited number of buildings are equipped with sub-metering that records hourly data, and in many cases even the main meters are not measured on an hourly basis. Older buildings often lack smart meters altogether, with energy use typically obtained from monthly readings. However, the revised EPBD (2024) introduces requirements for building automation and control in non-residential buildings [4]. In general, new buildings are equipped with more advanced metering systems, the data quality is improving, and future studies should be focus on data-driven and AI-based methods for energy performance

assessment, which are already appearing.

The operational hours adjustment methodology depends on different factors.. In Estonian national energy efficiency requirements, the typical operational hours are fixed for 12 commercial building type. This raises the question of how to choose the hours for buildings with multiple uses. In this study, the educational building had almost half its area occupied by offices and half by auditoriums and classrooms. The main results were calculated using both educational and office usage. However, when calculated using only educational usage, the primary energy use was 4 kWh/m^2 lower; for office usage alone, it was 8 kWh/m^2 higher than for mixed usage. This nearly 7% error influences the normalisation result, and therefore the choice of standard operational hours should be assessed carefully. One approach is to use the building type that represents the largest area in specific building. On other hand, this may not represent the actual energy use of the building. Therefore, the impact of selecting the occupancy hours should be investigated in future studies.

Normalising the heating energy use. When we come to adjusting the heating energy use according to standard operational hours, there should be careful with normalising. In this study, the heating energy use was mostly used by air handling unit and therefore, during operational hours, the heating demand was much higher than for non-operational hours. If we compare the normalised and STD model heating energy use, then the heating energy use of STD model is higher due to the dynamic effect, but normalisation do not capture it. It resulted, that the STD model heating energy use is very similar to metered energy use and is not much influenced by heat gains, as the main heat demand is due to air handling unit.

More realistic user profiles. To reduce the performance gap, energy performance assessments of existing building should be made more comparable to design phase calculations. However, this is only a partial solution. As Menezes et al. highlighted, design-phase energy performance assessment also needs to be more realistic considering post-occupancy evaluation. Their study showed a great reduction of the performance gap, reaching to only 3% gap instead of the two-third difference between simulation model and metered energy use. [26] Regarding after-hours work, NABERS provides guidance for offices [51], suggesting that its influence should be adjusted in asset ratings, since modern office buildings almost always exhibit a after-hours work arising from usage. This occurs because equipment is often left on standby overnight, and in some cases computational

processes continue after working hours (e.g., energy model simulations, extended calculations, or other computer processes), also the cleaning and security work. They suggest adjusting the after-hours schedule to 5% and 25%, respectively for lighting and equipment. Furthermore, Kim et al. presented a set of structured probabilistic statistical models for the prediction of internal electricity loads in non-residential buildings. [27] In conclusion, we adjust the typical building model requirements and apply the non-EPB and operational hours adjustment, the performance gap could be reduced. However, there should be also careful to not over normalise.

Limitations and future studies. This study addressed only the adjustment for non-EPB energy use, operational-hours correction, and climate correction. A limitation of this study is that the effect of usage-related loads (e.g., base load) were not considered. Furthermore, as these methods are tested in depth on three retail buildings and one multi-purpose building, the research should be expanded to include a larger number and broader variety of commercial buildings.

7. Conclusion

Quantifying and making energy performance gap visible is essential for better understanding the current state of the building stock. Moreover, actual performance should be assessed using metered energy use to reflect the real performance, thereby improving the asset rating methodologies as well as building energy performance benchmarks and thresholds. This study presents two newly formalised and reproducible approaches for handling non-EPB energy use considering tenant-level metering, and operational hours variability using metered data under EPBD constraints. The case studies are retail, wholesale buildings and one multi-purpose (office and educational) building.

The first method excludes energy uses not considered in the EPBD scope. However, as the non-EPB energy use is usually not measured separately in wholesale and retail buildings, tenant-level metering is used for this method. Specifically, tenant electricity with non-EPB uses was excluded and replaced with standard-based values for appliances and lighting. This approach resulted at least 50% reduction in primary energy use for three retail buildings case studies. The EPC changed by one or two classes and also made the performance gap visible if compared to the calculated EPC rating.

The second method adjusts metered energy use to align with standard operational hours. It is based on the average monthly power load during operational and

non-operational hours, derived from hourly data, and standard operational hours. Following normalisation, energy use decreased by 15 kWh/m^2 (11.8%) for electricity and 7 kWh/m^2 (10.9%) for heating primary energy use. Validation against a simulation model (derived with standard operational hours) showed only a 12 kWh/m^2 (7%) difference after applying the normalisation.

This study demonstrates the significant impact of non-EPB energy use and extended operational hours on non-residential building energy performance and how to consider it in the assessment. Further research should include additional case studies to consider the variations of small power loads and base load during non-operational hours in energy performance assessment. Moreover, the research should be expanded to include a larger number and broader variety of commercial buildings.

Overall, this study introduced new procedure with two practical and robust approaches that is currently needed in the market for adequately assessing building energy performance while excluding user behaviour and non-EPB energy use. Furthermore, these methods could help to distinguish between EPB and non-EPB uses and therefore improve understanding of building energy performance with the aim of enhancing it. These methods are also straightforward to apply in most commercial buildings.

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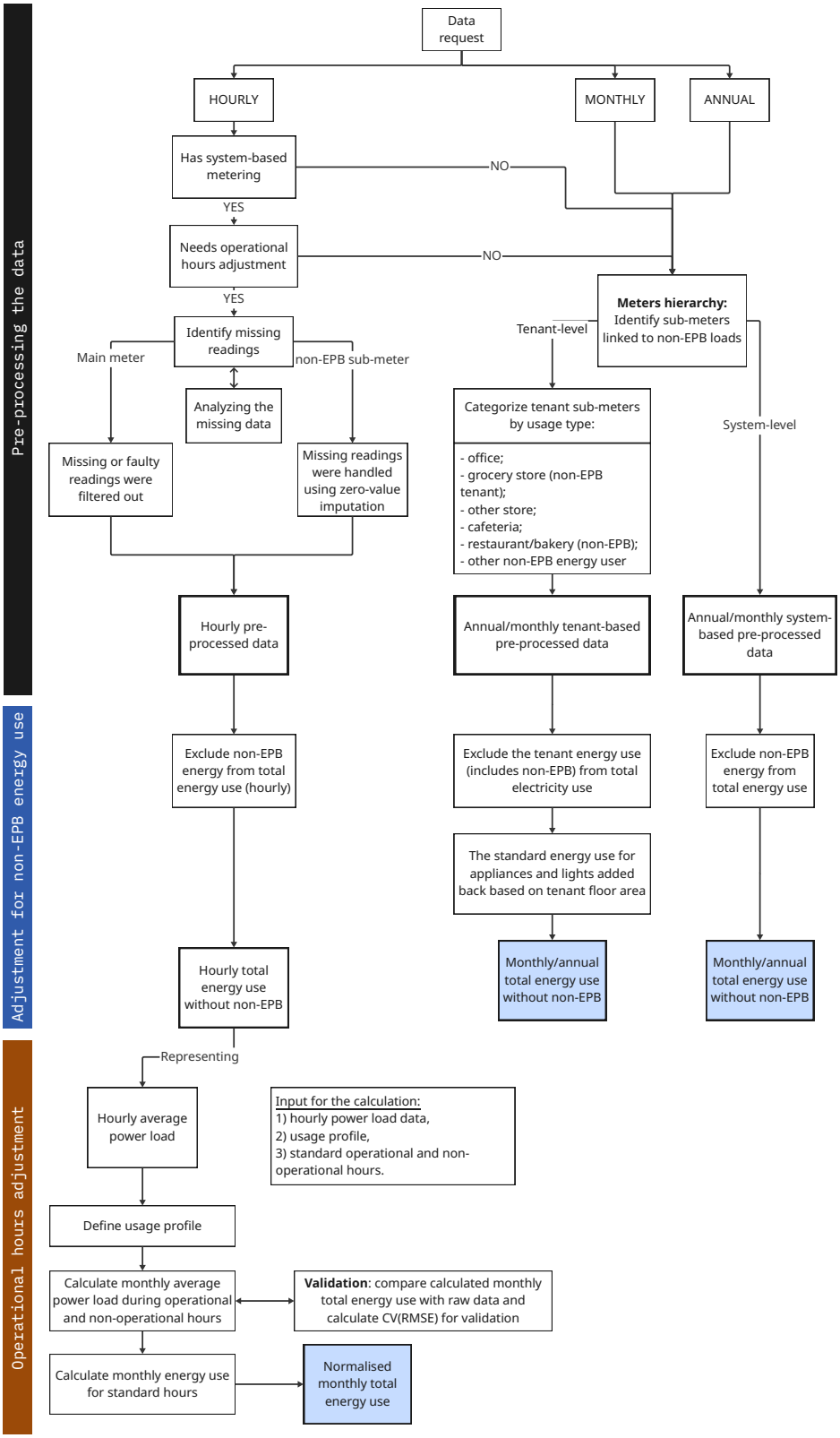
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Appendix A. The methodological workflow of Publication VI


Pre-processing the data
Adjustment for non-EPB energy use
Operational hours adjustment
Data request
HOURLY
MONTHLY
ANNUAL
Has system-based metering
NO
YES
Needs operational hours adjustment
NO
YES
Meters hierarchy: Identify sub-meters linked to non-EPB loads
Tenant-level
System-level
Identify missing readings
Main meter
non-EPB sub-meter
Analyzing the missing data
Missing or faulty readings were filtered out
Missing readings were handled using zero-value imputation
Categorize tenant sub-meters by usage type:
- office;
- grocery store (non-EPB tenant);
- other store;
- cafeteria;
- restaurant/bakery (non-EPB);
- other non-EPB energy user
Hourly pre-processed data
Annual/monthly tenant-based pre-processed data
Annual/monthly system-based pre-processed data
Exclude non-EPB energy from total energy use (hourly)
Exclude the tenant energy use (includes non-EPB) from total electricity use
Exclude non-EPB energy from total energy use
The standard energy use for appliances and lights added back based on tenant floor area
Hourly total energy use without non-EPB
Monthly/annual total energy use without non-EPB
Monthly/annual total energy use without non-EPB
Representing
Hourly average power load
Input for the calculation:
1) hourly power load data,
2) usage profile,
3) standard operational and non-operational hours.
Define usage profile
Calculate monthly average power load during operational and non-operational hours
Validation: compare calculated monthly total energy use with raw data and calculate CV(RMSE) for validation
Calculate monthly energy use for standard hours
Normalised monthly total energy use

Curriculum Vitae

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2014–2019	Tallinn University of Technology, School of Engineering, Heating, Ventilation, Air Conditioning and Refrigeration Engineering Technology, MSc
2011–2014	Saaremaa Co-Educational Gymnasium
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4. Language competence

Estonian	Native language
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6. Voluntary work

2025–…	Member of the Senate and Committee for Research at TalTech
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2015–2017	Youth Organisation of Estonian Society of Heating and Ventilation Engineers
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7. Field of research

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8. Scientific work
Papers

1. H. Kuivjõgi, M. Thalfeldt and J. Kurnitski. Metered Energy Normalization in Non-residential Buildings for Compliance Assessment with EPBD Minimum Energy Performance Standards. In *Proceedings of the 15th REHVA HVAC World Congress – CLIMA 2025. Vol. 2*. Cham, Switzerland: Springer, 2026, pp. 880–889. DOI: 10.1007/978-3-032-06810-1_89.
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2. H. Kuivjõgi, H. Sarevet, M. Thalfeldt and J. Kurnitski. *Heat recovery ventilation solutions for school building renovation: case study*, CLIMA 2022: 14th REHVA HVAC World Congress, 22–25 May 2022, Rotterdam, The Netherlands.

3. H. Kuivjõgi, J. Laaneste, M. Thalfeldt and J. Kurnitski. *Heat recovery ventilation system heating energy weather normalization – calculation method and case study*, BuildSim Nordic 2022, 22–23 August 2022, Copenhagen, Denmark.

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3. Haridus

2020–…	Tallinna Tehnikaülikool, inseneriteaduskond, ehituse ja arhitektuuri instituut, doktoriõpingud; juhendajad prof Jarek Kurnitski ja prof Martin Thalfeldt
2014–2019	Tallinna Tehnikaülikool, inseneriteaduskond, hoonete sisekliima ja veetehnika, MSc
2011–2014	Saaremaa Ühisgümnaasium
2002–2011	Lümanda Põhikool

4. Keelteoskus

eesti keel	emakeel
inglise keel	kõrgtase

5. Teenistuskäik

01.01.2026–…	Tallinna Tehnikaülikool, Inseneriteaduskond, Ehituse ja arhitektuuri instituut, ekspert
01.02.2021–01.01.2026	Tallinna Tehnikaülikool, Inseneriteaduskond, Ehituse ja arhitektuuri instituut, doktorant-nooremteadur
16.09.2019–31.01.2021	Tallinna Tehnikaülikool, Inseneriteaduskond, Ehituse ja arhitektuuri instituut, ekspert
01.01.2018–01.11.2018	O3 Inseneribüroo, projekteerija

6. Vabatahtlik töö

2025– …	Tallinna Tehnikaülikooli senati ja teaduskomisjoni liige
2016–2017	Ehitusteaduskonna Üliõpilasnõukogu haridusvaldkonna aseesimees
2015–2017	Eesti Kütte- ja Ventilatsiooniinseneride Ühenduse noorteorganisatsioon
2015– …	Eesti Kütte- ja Ventilatsiooniinseneride Ühendus

7. Teadustöö põhisuunad

- CERCS-i teadusvaldkond: T230 hoonete ehitus.
- Hoonete sisekliima ja energiatõhusus.

8. Teadustegevus

Teadusartiklite, konverentsiteeside ja konverentsiettekannete loetelu on toodud ingliskeelse elulookirjelduse juures.

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