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# Evaluating building-level parameters for lower-temperature heating readiness: A sampling-based approach to addressing the heterogeneity of Dutch housing stock

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A B S T R A C T

The Dutch government aims to eliminate natural gas for residential heating in 1.5 million homes by 2030. One strategy is connecting existing dwellings to lower-temperature district heating (DH) systems, although these dwellings might require energy renovations. The heterogeneous dwelling stock causes varying renovation needs that complicate the energy transition. The present study addresses this issue by assessing the building-level parameters affecting the readiness of the Dutch terraced-intermediate and apartment types for lower-temperature heating (LTH) supplied by DH systems. A sampling-based approach was employed to capture variability within these dwelling types, addressing the limitations of archetype-based methods. The findings suggest a sample size of 1300 to represent the variations in these dwelling types. Parametric simulations and machine learning methods were used to identify significant building-level parameters for medium-temperature (MT: 70/50 °C) and low-temperature (LT: 55/35 °C) supply levels. These include heating setpoints (desired indoor temperature) and ventilation-related parameters (ventilation system type and air infiltration rate), followed by fabric-related parameters (roof, glazing, wall, ground, and door insulation) and geometric properties (orientation, compactness ratio, and window-to-wall ratio). Additionally, radiator oversizing also impacts LTH readiness. These results broadly apply to the studied dwelling types, although feature importance varies by supply temperature and dwelling type. The findings can guide stakeholders in assessing current conditions and prioritising renovation measures, aiding the development of targeted renovation solutions. Encompassing the representative variations within studied dwelling types enhances the robustness of the results. However, incorporating more refined data could improve the accuracy of the findings, better supporting the energy transition of these dwellings.

## 1. Introduction

The built environment is currently responsible for 30 % of global energy consumption [1], with 15 % of this energy being used for space heating and hot water [2]. In 2022, fossil fuels accounted for 60 % of the heating energy demand, resulting in direct $CO_2$ emissions of 2400 megatonnes [2]. Therefore, it is imperative to explore fossil-free approaches for decarbonising the building heating sector. The Dutch government has set an ambitious target to eliminate the use of natural gas for domestic heating in 1.5 million existing homes by 2030 [3]. For this transition, lower-temperature district heating (DH) systems are emerging as a viable solution to provide sustainable heat to densely populated areas [4–6]. Unlike traditional DH systems, these operate with supply temperatures below 75 °C, allowing for the integration of various sustainable heat sources, such as geothermal, aqua thermal, residual heat from industry, data centres, supermarkets, and solar thermal plants, as alternatives to natural gas [7,8]. Additionally, lower supply temperatures improve the efficiency of heat distribution networks [8,9] and enhance thermal comfort at the building level [10,11]. Currently, only 6.4 % of Dutch homes are connected to DH systems [12,13], although it is estimated that by 2050, nearly 50 % of sustainable heat will be supplied through them [14]. In due course, many existing dwellings will be connected to lower-temperature DH systems.

The transition of existing dwellings to these lower-temperature DH systems often requires energy renovations [7,15,16], which involves complex decision-making due to the involvement of multiple stakeholders with conflicting objectives [17–19]. This complexity is further

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**Nomenclature**

| | |
|---|---|
| DH | District Heating |
| GSA | Global Sensitivity Analysis |
| HBjson | HoneyBee Json |
| HT | High-Temperature |
| LHS | Latin Hypercube Sampling |
| LT | Low Temperature |
| LTH | Lower Temperature Heating |
| MFH | Multi-Family House |
| MT | Medium Temperature |
| PDFs | Probability Density Functions |
| RF | Random Forest |
| SFH | Single-Family House |
| SRRC | Standardised Rank Regression Coefficient |
| TRY | Test Reference Year |
| UBEM | Urban Building Energy Modelling |
| Als | External Heat Loss Area [$m^2$] |
| Ag | Total Usable Heated Area [$m^2$] |
| $Q_{v10}$ | Air infiltration rate at 10 PA [$dm^3/s.m^2$] |
| $Q_{v10;spec}$ | Specific air infilteration rate for a building type at 10PA [$dm^3/s.m^2$] |
| $f_{type}$ | Dimensionless correction factor for building type |
| $f_y$ | Dimensionless correction factor for construction year |
| $Ø$ | Radiator heating power at new temperature set [W] |
| $Ø_0$ | Radiator heating power at original design temperature set [W] |
| $\Delta T$ | Logarithmic mean temperature difference at new temperature set [℃] |
| $\Delta T_0$ | Logarithmic mean temperature difference at original design temperature set [°C] |
| $n$ | Radiator exponent [-] |
| $T_s$ | Radiator supply temperature [°C] |
| $T_r$ | Radiator return temperature [°C] |
| $T_i$ | Design indoor temperature [°C] |
| $R^2$ | Coefficient of Determination |

compounded by the heterogeneity of the dwelling stock, resulting in varying renovation needs that require individual assessments and customised solutions [20–22]. Nevertheless, developing assessment models for the entire stock at the individual dwelling level is challenging due to the limited data availability and the computational resources required to analyse them [23–27]. Consequently, studies typically employ reference or archetype buildings to represent the national stock [25,28,29]. These archetypes are developed through statistical analyses and the clustering of common building features such as construction period, type, size, HVAC systems and occupant profiles within specific building categories [25,28,30,31]. While these archetypes are beneficial for estimating energy-saving potential and assessing the cost-effectiveness of renovation measures at a policy level [25,32], they introduce uncertainties due to the averaging of variations within dwelling types [21,31]. As a consequence, these uncertainties may result in a performance gap between the expected outcomes, based on archetypes, and the actual performance of individual dwellings [21,33].

A systematic review conducted by the authors [34] found that current scientific literature relies on archetypes, or specific cases, for evaluating the renovation measures needed for lower-temperature heating (LTH) in residential buildings. As a result, analysis of variations due to building characteristics within the dwelling types is not taken into account when assessing the readiness of the dwelling stock for LTH, highlighting a significant knowledge gap. This gap is particularly crucial for stakeholders such as municipalities and housing corporations who manage diverse portfolios and require insights to determine which dwellings are prepared for LTH, those which necessitate renovations for LTH implementation, and where priorities should be established. These challenges correspond to the information barrier impeding energy renovation projects [35,36].

In this context, recent studies have conducted extensive measurement campaigns encompassing the diversity of the dwelling stock. For instance, the study conducted by Østergaard et al. [37] analysed survey data from 1,645 single-family houses (SFH) and apartments in Denmark to evaluate the oversizing of radiators and their suitability with low-temperature supply from DH systems. Similarly, Pothof et al. [38] measured 220 existing dwellings that were representative of the Dutch dwelling stock with natural gas heating systems. These dwellings were examined to determine the minimum supply temperature required without any renovations under design conditions, as well as to assess their suitability for lower supply temperatures. While these studies provide valuable insights, they encounter limitations due to uncertainties from manual data entry and measurement errors. Moreover, such comprehensive approaches, though ideal, are expensive and time-intensive [39]. To address this, several researchers propose a statistical sampling-based approach [32,40–42]. Compared to the traditional archetype-based method, representative samples that reflect the variations in the dwelling types can be generated and facilitate quicker evaluations than extensive measurements or surveys of dwellings.

### 1.1. Research gap and aim of the study

Existing dwellings in the Netherlands require energy renovations to use LTH from DH systems. However, the heterogeneous nature of the dwelling stock complicates the decision-making process concerning the selection of the appropriate renovation solutions. Current research reveals specific gaps in understanding the requirements for transitioning these dwellings to LTH. Firstly, most studies rely on archetype-based approaches, which are inadequate for addressing the variations within dwelling types. Consequently, these approaches create information barriers for stakeholders, as they are limited in providing detailed insights into diverse dwellings. Secondly, while direct measurement and surveying of buildings offer detailed information, they are resource-intensive and time-consuming, making them impractical for large-scale assessments.

Given these challenges and gaps identified in the existing knowledge base, the primary objective of this study is to evaluate how the diversity within the dwelling stock can be incorporated into the assessment of LTH readiness in the Netherlands. By acknowledging the heterogeneity of dwellings, this study aims to provide a nuanced analysis of building-level parameters that influence LTH readiness. To achieve this, the study employed the sampling-based approach. This approach offers a robust framework to strategise suitable energy renovations for preparing Dutch dwellings for LTH supplied by DH systems.

### 1.2. Related studies on sampling-based approach

Previous applications of the sampling-based approach have demonstrated its utility in energy renovation research. For instance, according to Liang and Shen [40], surveying and measuring energy consumption is not always feasible for all the buildings in an area. Therefore, they proposed a sampling-based approach to generate representative data and concluded that simulations based on such data could yield valuable insights, provided that an appropriate sample size is used. Further, Brown et al. [41] utilised statistically representative samples derived from comprehensive survey data collected across Sweden's building stock. A sample of 1400 multi-family homes (MFH) and single-family homes (SFH) were analysed to assess the embodied global warming potential of renovation measures that reduce operational energy consumption.

Furthermore, an approach for investigating the cost-optimality of energy renovations in the presence of variations within a building category is proposed by Mauro et al. [32]. The authors introduced a methodological framework called *SLABE* that leveraged statistical and probabilistic methods for generating representative samples of a dwelling type (referred to as reference building samples) instead of the single archetype (referred to as a reference building). Moreover, a comprehensive review by Mastrucci et al. [26] on the lifecycle assessment of building stock identified the convenience of modelling representative samples, compared to a *building-by-building* approach, in capturing the broad variability of the building stock. Additionally, Baldini et al. [21] assessed building samples to investigate energy-efficient and cost-effective renovation measures for a DH area in Denmark, which were tailored to diverse building characteristics instead of archetypes. Their study ascertained that the heterogeneous approach could provide valuable insights that might have been overlooked in an archetype-based approach.

Further, Jaeger et al. [42] discussed the limitations of the archetype-based approach for Urban building energy modelling (UBEM). They proposed an approach to characterise the buildings in a UBEM through probability density functions (PDFs) defined for key parameters. As per the authors, the PDFs can be statistically defined, including the renovation probability for estimating the possible building values, thus generating realistic variations for existing dwelling stock. In recent studies [27,43], the authors utilised sample-based approaches to generate represented data and train machine learning models to predict energy consumption and identify the essential features that can assist in prioritising renovation strategies.

### 1.3. Methodology and outline

While the literature suggests that sampling-based approaches could provide a more feasible solution to address heterogeneity, these approaches have not yet been applied to assess the diversity of dwellings in the Netherlands concerning their readiness for LTH. Therefore, to address the research aim, the methodology employed consists of two components: 1) determining the appropriate sample size to adequately represent the variations in dwelling type, and 2) identifying the significance of building-level parameters in assessing the readiness of a dwelling for LTH, while accounting for the variations. This approach will be applied to terraced-intermediate and apartment dwelling types, which constitute a substantial portion of SFH and MFH in the Netherlands. Section 2 presents these selected dwelling types and discusses their representation in the national building stock. Following this, Section 3 outlines the methodological framework, detailing the parametric simulation workflow, the generation and identification of appropriate sample size, dataset labelling and the application of supervised machine learning in predicting a dwelling's readiness for LTH. In this study, the LTH refers to heat supplied at Medium Temperature (MT: 70/50 °C) and Low Temperature (LT: 55/35 °C) levels compared to the High Temperature (HT: 90/70 °C) supply. Sections 4 and 5 describe the results and provide insights into the appropriate sample size required to represent variations in dwelling types. They also discuss the relative importance of the input features extracted from the machine learning model. Finally, Section 6 summarises the study's findings and limitations.

The novelty of this study lies in two main aspects: 1) a sampling-based approach in generating a dataset representing the variations found in SFH and MFH in the Netherlands. Such datasets can be utilised in future research endeavours aiming to explore solutions for the energy transition of existing residential stock, 2) the identification of the parameters that significantly influence a dwelling's readiness for LTH while accounting for the variations within the dwelling type. The study argues that incorporating these variations ensures robustness in assessing the implications of these parameters. Moreover, these parameters can serve as a guide for strategising renovations aimed at preparing dwellings for LTH. Consequently, they can assist stakeholders with diverse portfolios in effectively selecting renovation strategies to decarbonise their portfolio by transitioning to LTH supplied by DH systems fuelled by sustainable heat sources.

## 2. Overview of dwelling types

The Dutch dwelling stock comprises a variety of typologies influenced by different construction years and distinctive architectural features. This stock is categorised into 16 types, segmented by four construction periods and four dwelling types, as depicted in Fig. 1. The dwelling types are clustered into two main categories: SFH, which includes terraced-intermediate, corner and detached houses, and MFH, encompassing various apartment typologies [44]. The term 'intermediate' refers to a dwelling situated between two others, whereas the 'corner house' category comprises terraced houses located at the end of row houses and the semi-detached typology, commonly known in Dutch as "*twee onder een kap*" (two under one roof). The apartment category broadly includes maisonettes, walk-ups or porches, gallery and flats types. A more detailed sub-type of apartments, based on their position within the residential block, is provided in [45].

The categorisation of construction periods reflects the diverse constructional practices and building regulations over the periods considered. For instance, dwellings built before the 1970s have poor energy performance, having been constructed prior to the adoption of thermal regulations [34,38]. In contrast, stricter building regulations to improve energy performance in the Netherlands were introduced in 1991 [46]. A recent housing survey in the Netherlands revealed that dwellings constructed before the 1980s typically have energy labels C or worse, indicating higher energy demands for such houses [47]. These dwellings may present challenges when connecting to DH systems with lower temperature supply [7].

In addition, Fig. 1 illustrates the distribution of dwelling types across each construction period and within the existing dwelling stock. Comprising 66 %, SFHs constitute the majority of the stock, while MFHs make up the remainder. Due to time constraints, this study focuses explicitly on terraced intermediate houses, which represent 26.6 % of the stock, and apartments, which account for 33.4 %. By focusing on these two types, the study aims to examine a substantial portion of the dwelling stock, characterised by a diverse range of building characteristics, to identify the significant features that determine their suitability for LTH.

## 3. Materials and methods

This section outlines the methodological steps for analysing variations within a specific dwelling type in the Netherlands, when aiming to assess the influence of building characteristics on the readiness of the dwellings to operate at lower temperature supplies from DH systems. The study first identified key building-level parameters, referred to as interest parameters, which affect both the variations within dwelling type and their readiness for LTH. A sampling procedure was employed to generate diverse samples in order to systematically assess these interest parameters, thus capturing the variations within the dwelling type. These samples were subsequently examined through a parametric workflow to simulate annual space heating demand and underheated hours when the dwellings were occupied. Notably, these output parameters are central to the LTH-readiness definition established in our previous work [16].

Identifying an appropriate sample size to represent these variations within the dwelling type is essential to this study. To accomplish this, the sample size was incrementally increased until the effects of the interest parameters on the two output parameters converged. The Standardised Rank Regression Coefficient (SRRC), a global sensitivity analysis


**Fig. 1.** Categorisation of housing stock. The Figure illustrates the categorisation of housing stock based on four dwelling types and their respective share in each construction year and in the total existing housing stock [44,45].

(GSA) method, was used for this purpose. Subsequently, the identified sample size was used to generate representative samples, which were subjected to simulations at HT (90/70 °C), MT (70/50 °C) and LT (55/35 °C) supply temperatures. Using the LTH-readiness definition, these samples were classified as either "ready" or "not ready" for both MT and LT supply temperatures.

In addition, the representative sample datasets with binary classifications, for MT and LT supply, were used to train the ensemble-based Random Forest (RF) classifier model. The RF models facilitated the extraction of the relative importance of the interest parameters for each dwelling type. This analysis underscores the significance of the building-level parameters in determining the readiness of the dwelling type for both MT and LT supply while also accounting for variations due to these parameters. Fig. 2 visually describes the methodological steps applied to both terraced intermediate and apartment dwelling types, with corresponding sub-sections providing further explanation. Conversely, Figure A.1 in the Appendix presents a detailed process workflow used in this study.

### 3.1. Interest parameters

This section describes the identified dwelling characteristics that introduce variability within dwellings as well as affect their readiness for LTH. These variations, resulting from specific interest parameters, contribute to the heterogeneity of the dwelling stock. The parameters that characterise a dwelling can broadly be categorised into geometry, fabric, system and occupancy controls [32,48]. Geometrical properties encompass the physical attributes of a dwelling, such as shape, orientation, floor area, window-to-wall ratio and position (particularly in apartment settings) [49]. Fabric properties refer to the thermo-physical characteristics of both the opaque and transparent components of the building envelope [27]. System parameters are concerned with the heating, ventilation and air-conditioning (HVAC) systems and their operational management. Lastly, the occupancy parameters focus on the presence of occupants and their behavioural actions [48].

The systematic literature review in our recent study [34] identified the essential building characteristics that influence the potential for implementing LTH and the necessity for renovations. These characteristics include the compactness ratio, which represents the geometrical relationship between dwelling shape, position and surface area; thermal insulation of the building envelope; ventilation system and airtightness; and the capacity of the existing space heating system as per the supply temperature level. Additionally, indoor heating setpoints were indicated as a parameter reflecting the occupant's preference for indoor comfort. As a result, combining these studies, Table 1 illustrates the interest parameters that characterise a dwelling as well as impact its LTH readiness.

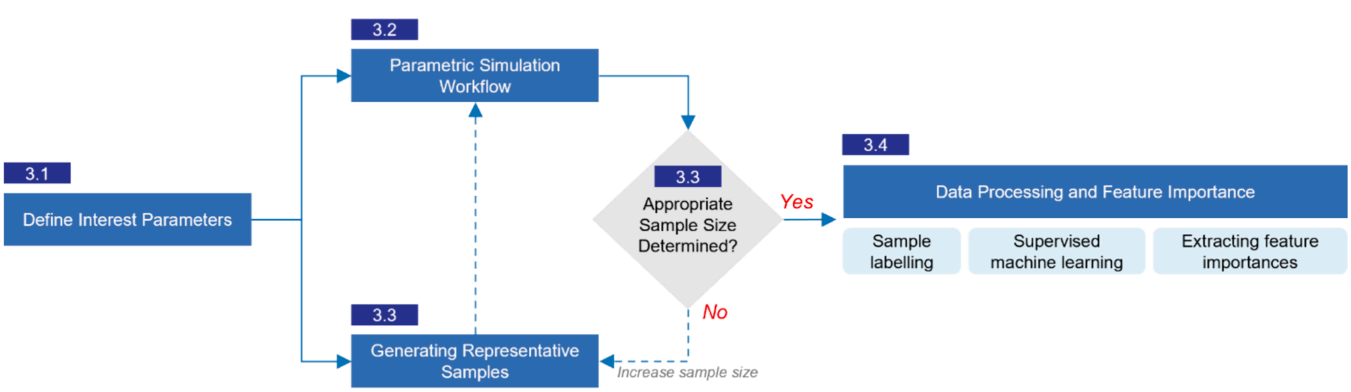


**Fig. 2.** Methodological steps applied to terraced intermediate and apartment dwelling types, with the corresponding sub-section providing further explanation.

**Table 1**
Interest parameters that characterise a dwelling and have an impact on LTH readiness [32,34,48,49].

| Category | Input Parameter | Units |
|---|---|---|
| Geometrical | Orientation | ° |
| | Compactness-Ratio | – |
| | Window-to-Wall Ratio | – |
| | Position of Apartment* | – |
| Fabric | Ground Insulation, R | $m^2 \cdot K/W$ |
| | External Wall Insulation, R | $m^2 \cdot K/W$ |
| | Roof Insulation, R | $m^2 \cdot K/W$ |
| | Glazing Insulation, U | $W/m^2 \cdot K$ |
| | External Door Insulation, U | $W/m^2 \cdot K$ |
| | Infiltration | $dm^3/s.m^2$ |
| HVAC | Ventilation system | – |
| | Heating Capacity | W |
| Occupant and Control | Heating setpoint | °C |

*Only for apartment typology.

These parameters are utilised to develop the simulation workflow, as described in the subsequent section, and the sampling procedure is used to generate samples by varying them, as detailed in Section 3.3.

### 3.2. Parametric simulation

The interest parameters outlined in the previous section informed the development of the parametric simulation workflow, which is designed to process batches of samples produced by the sampling procedure (described in Section 3.3). The workflow was developed within the Rhino-Grashopper v7 environment with Ladybug Honeybee tools v1.6, which facilitated the translation of Rhino geometry into a multi-zone building energy model. In addition, the samples from the sampling procedure in an Excel file were imported into the grasshopper environment, where an iterator using the Colibri plugin v2.0 was used to run through each sample. Each interest parameter interacted with a seed model that represented a typical geometry and internal layout of the dwelling type. Depending on the values of each interest parameter, the seed model was altered to represent a dwelling case, based on the sample. After generating all the samples, they were simulated in the cloud, and the results were recorded in an Excel output file. This section discusses the development of the seed model, model validation, and cloud computing integration, as shown in Fig. 3. The Grasshopper and Python scripts developed are open-source and can be accessed through the open-source repository [50].

#### 3.2.1. Generating seed model

*3.2.1.1. Geometry.* The seed models illustrate the typical geometry and internal layout of terraced and apartment dwellings, as described in Section 2. Further, the geometric model for the terraced dwelling was developed using typical plans obtained from [51,52]. These studies indicate that despite representing newer construction, existing dwellings generally share the same layout. Conversely, a typical layout of walk-up apartments (referred to as "*portiekwoning*" in Dutch) was used for the apartment typology. Such apartment types were widespread during the post-war period [53–55]. The layouts used to generate these geometries can be found in Figure B.1 in the Appendix.

Even though these models represent the standard geometry and layout of the dwellings, variations in dwelling size exist. These variations were incorporated using the compactness ratio parameter. According to the Dutch Technical Agreement (NTA8800) [56], the compactness ratio is defined as the ratio between the heat loss envelope surface area (Als) and the total usable heated area (Ag). This ratio serves as a metric for assessing the impact of dwelling size on heat losses and heating demands. Within Dutch regulations, the compactness ratio (Als/

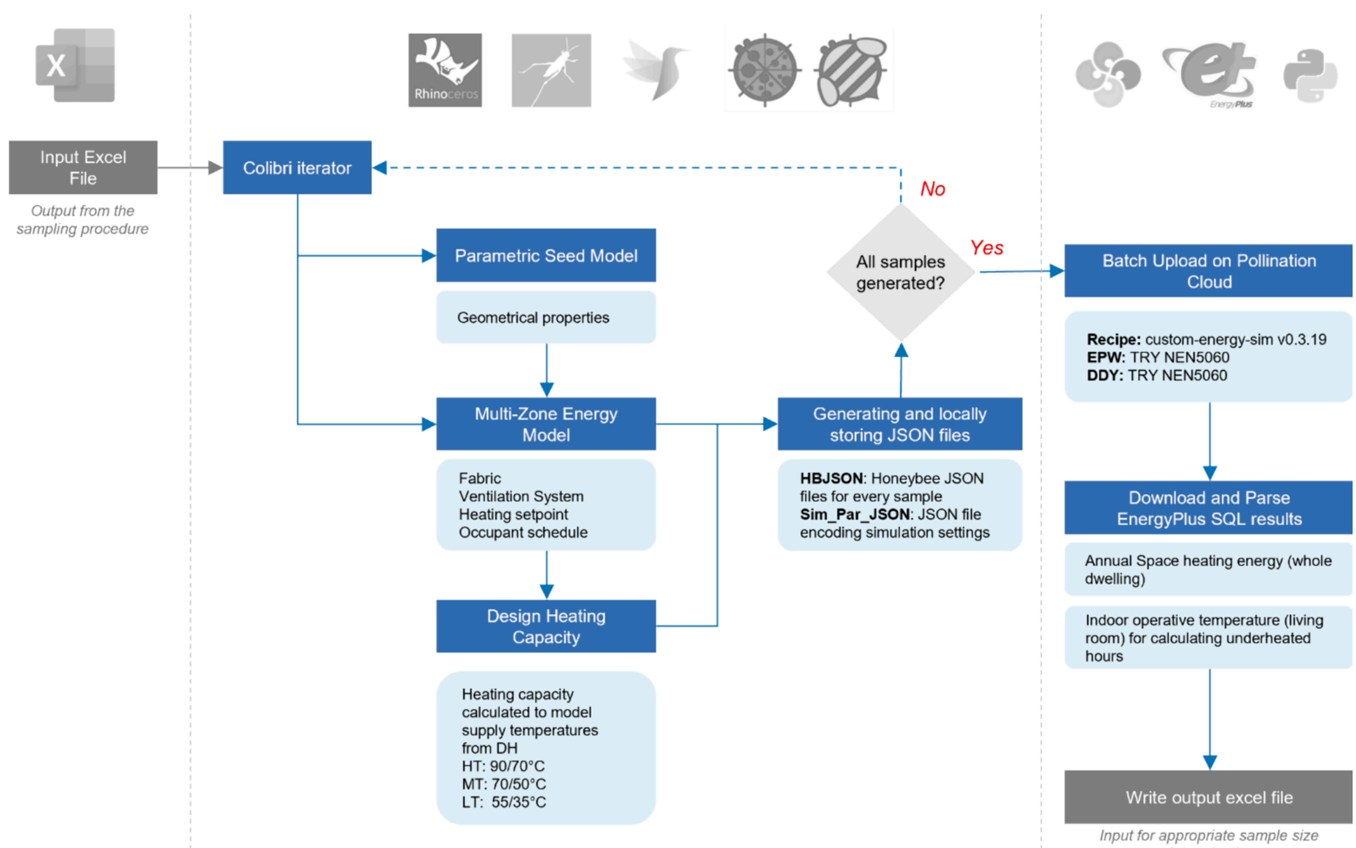


**Fig. 3.** The parametric simulation workflow to simulate the batch of samples.

Ag) plays an essential role in establishing benchmarks for new construction to achieve nearly zero energy standards [52,57] and in defining the insulation standards for existing dwellings [58].

In the parametric workflow, the sampled compactness ratio is utilised to proportionally adjust the length of the seed model to reflect the variation in the dwelling size. For both dwelling types, a geometric relationship was formulated between the compactness ratio and the length of the seed model while keeping the width and height fixed. Compared to a terraced house, this relationship for apartment typology also reflects its possible positions within the apartment block itself. Nevertheless, it should be noted that in some instances, the sampled compactness ratio may result in unrealistic lengths. Therefore, limits were imposed on the calculated length to mitigate this issue and prevent such samples. Appendix C describes the geometric relationship and the corresponding calculations.

*3.2.1.2. Fabric.* Once the geometry of the seed model is adjusted to represent the sample, thermal insulation values are assigned to the ground floor, external wall, roof, glazing, and doors. Additionally, the airtightness of the building envelope is assigned as the infiltration rate. In the absence of measured values, the NTA8800 [56] provides a calculation method to estimate the infiltration rate, taking into account different building types. The calculation method is illustrated in Equation (1), where $Q_{v10}$ represents the calculated air infiltration rate, and $q_{v10;spec}$ represents the specific infiltration rate for a building type at a uniform pressure of 10 Pa. The dimensionless correction factor due to building type and position is denoted by $f_{type}$, while the correction factor due to construction year is represented by $f_y$.

$$Q_{v10} = f_{type} \times f_y \times q_{v10;spec} \left[\frac{dm^3}{s.m^2}\right] \tag{1}$$

*3.2.1.3. HVAC and occupant control. Ventilation system*

In the Netherlands, the three prevalent ventilation systems are A, C and D [45]. System A utilises a natural ventilation system through openings, whereas System C integrates mechanical extract with natural intake [59]. System D, also referred to as a balanced ventilation system, features mechanical intake and extraction and is often combined with a heat recovery (HRV) system [59]. Variants within systems C and D, such as demand-driven or $CO_2$-controlled, can also be found for specific ventilation needs.

The simulation workflow involves maintaining a minimum ventilation rate for each space as mandated by the Dutch building decree [60]. System A regulates this rate by operable apertures, with the control operation as per ISSO 32 [61] guidelines. In contrast, the demand-driven variant of system C adjusts the ventilation based on the occupancy schedule. For modelling system D, the study adopts the approach suggested by Alavirad et al. [52], where a reduced ventilation rate serves as a proxy for a balanced ventilation system equipped with HRV. This adjustment rate is based on the HRV system's typical efficiency of 90 %. However, this study adopts a conservative estimate by reducing the ventilation rate to be maintained by 50 %. Consequently, only half the fresh air requires treatment, while the HRV system recovers the other half. This simplification aids in modelling the ventilation systems without complex calculations, focusing primarily on the impact on space heating energy. Nevertheless, it does not account for the operational energy of the system itself and might lead to oversimplification.

*Modelling lower supply temperatures from DH systems*

When the supply temperature is lowered, the heating capacity of existing space heating systems, such as radiators, is also reduced [16,62,63]. In dwellings with a high heating demand due to heat losses, the reduced capacity of the space heating system may be insufficient to offset these losses, potentially causing thermal discomfort to the occupants. Therefore, in this study, design heating capacities are used as a proxy to simulate the effect of supply temperature. Thus, the heating capacities for heated zones are calculated based on steady-state heat loss from ventilation and transmission under design conditions of −10 °C outside and 20 °C inside, excluding solar and internal heat gains [64]. At this stage, the design heating capacity is considered the same as the theoretical heat loss without oversizing. The calculated heating capacity represents the design capacity of the individual zones in the HT supply, and can be reduced further depending on the lower supply temperature levels, which in this study are MT(70/50 °C) and LT(55/35 °C). This reduction is calculated using Equations (2) and (3) [65] to evaluate the LTH readiness.

$$\varnothing = \varnothing_0 \times \left(\frac{\Delta T}{\Delta T_0}\right)^n \tag{2}$$

$$\Delta T = (T_s - T_r)\left[\ln\left(\frac{T_s - T_i}{T_r - T_i}\right)\right]^{-1} \tag{3}$$

In these equations, $\varnothing$ and $\varnothing_0$ are the radiator heating capacity in watts and $\Delta T$ and $\Delta T_0$ are the logarithmic mean temperature differences at the new and original temperature sets, respectively. The radiator exponent '*n*' is fixed at 1.33. In addition, $\Delta T$ is calculated using the supply and return temperature ($T_s$ and $T_r$, respectively) in °C and the indoor design temperature ($T_i$) is set to 20 °C.

*Heating setpoints and occupant schedule*

According to the study by Guerra-Santin and Silvester [66] on Dutch household occupancy and heating profiles for building simulations, a consistent heating schedule for the entire week can simplify the simulation process. Consequently, this study applies a constant heating setpoint temperature to the living room and kitchen, while a two-degree heating setback is used in bedroom spaces. Cooling systems are not yet standard in Dutch dwellings, although a setpoint of 24 °C is used for cooling [52,61]. This study also assumes an average occupancy of three people, representing a typical nuclear family, with a combined equipment and lighting load of 4 W/m$^2$ [52].

*3.2.1.4. Simulation outputs.* The simulation models generated for each sample were simulated annually using the test reference year (TRY) recommended by NEN 5060 [67]. Building on the LTH-ready criteria defined in our previous research [16], a sample qualifies as LTH-ready if it maintains or improves the space heating demand and reduces thermal discomfort at lower temperatures relative to the original HT supply. As a result, annual space heating energy normalised for the total heated area (kWh/m$^2$), serves as a key performance indicator (KPI) to assess space heating demand. Additionally, the study evaluates thermal discomfort by calculating the occupied cold hours below the 20 % predicted percentage dissatisfied threshold, defined here as underheated hours, and based on the method proposed by Peeters et al. [68].

While the space heating demand is calculated for the entire dwelling, underheated hours are evaluated specifically for the living room. Given that occupants spend the majority of their time in the living room, it can act as a proxy for assessing the thermal comfort of the entire dwelling in the presence of lower temperatures. This approach is supported by findings from our previous research [16]. For determining occupied underheated hours, it is assumed that the living room is occupied for 5840 h annually from 8:00 to 23:00.

*3.2.2. Model validation*

The models developed from the described workflow are contingent on the accuracy of the outcomes. Therefore, validating the outcome from the simulation workflow is essential. For this purpose, this study utilised the average properties of terraced and apartment dwellings from four construction periods, as provided by the study done by Cornelisse et al. [44] on insulation standards for Dutch existing dwellings. In addition, the same study details the average space heating demand of these dwelling categories across different construction years. Since there is a lack of reference data for underheated hours, this study will use the average space heating demand for validation from [44]. A deviation of up to 20 % is considered acceptable for validation, accounting for differences in assumptions and calculation methods. Further, Table 2 outlines the data used as input to validate the simulation workflow.

#### 3.2.3. Cloud computation

One essential aspect of developing the workflow was accelerating the simulation process, allowing for rapid testing of various sample sizes. To achieve this, the study leveraged the Pollination cloud computing service for faster simulation [69]. The multi-zone model of every sample incorporating the geometrical details, fabric, systems and controls was exported into a honeybee Json (HBjson) file format (Fig. 3). These files were uploaded to the cloud server using the Pollination API and processed using the validated recipe "custom-energy-sim" v0.3.19. Upon completion of the simulations, the EnergyPlus outputs were retrieved as SQL files and parsed within the Grasshopper environment to compute normalised space heating energy demand and underheated hours.

### 3.3. Generating representative samples

As previously discussed, the heterogeneity of the dwelling stock introduces uncertainties regarding their readiness for LTH and the need for appropriate renovation options. Compared to the standard archetype, these uncertainties arise due to the inherent variations within each dwelling type [42,70]. To capture this diversity, samples that reflect these variations within specific dwelling types are generated. This section describes the systematic approach for creating these samples based on the interest parameters, as detailed in section 3.1. Additionally, it details the method used to determine the appropriate sample size required to represent the variability within the dwelling types.

#### 3.3.1. Systematic sampling approach

Probabilistic sampling is a standard practice in conducting uncertainty and sensitivity analyses, as documented in the literature [71–73]. The uncertainties due to input parameters are typically characterised using ranges and PDFs defined at the individual building level. These uncertainties are incorporated through sample generation to evaluate their impact on the model outputs [49,73,74]. In contrast, this study extends the application of ranges and PDFs for interest parameters to cover the full spectrum of dwellings within the same type. Further, this approach allows the incorporation of inherent diversity among the same residential type, providing a broader analysis of variations within the dwelling stock.

A notable challenge in developing representative samples within a dwelling type is the potential creation of unrealistic combinations. For instance, samples might be configured with a balanced ventilation and heat recovery system alongside minimal insulation, combinations that are unlikely to exist in practice. To address this issue, the present study adopted a group sampling procedure with unequal proportion sampling, as discussed by Liang and Shen [40]. This approach involves classifying samples prior to actual sampling in order to enhance their representativeness. Consequently, a systematic multi-level sampling scheme was developed, where the sampling method initially selects the construction year category based on its discrete probability distribution. Further, this distribution is derived from the unequal proportion of the dwelling type across each construction year category. The PDFs and ranges of each interest parameter are subsequently varied according to the construction year class. After selecting the construction period, the sampling method employs the specific ranges and PDFs associated with that period to generate realistic samples.

Nevertheless, it is essential to note that the construction year category does not determine whether a house is ready to utilise LTH from DH systems [34,38]. Many dwellings, particularly those built before the Second World War, are likely to have undergone renovations or periodic maintenance [45]. Therefore, the ranges and PDFs developed for each interest parameter of terraced and apartment dwelling types across the four construction categories represent the current condition of the dwellings. Fig. 4 illustrates the multi-level sampling approach. The distribution and ranges of interest parameters for four construction year categories are based on data from the 2018 National Housing Survey (Woon database) [44,45]. The data is organised separately in Tables D.1 to D.10 for terraced-intermediate and apartment dwellings in Appendix D.

Furthermore, the multi-level sampling approach utilises the Latin Hypercube Sampling (LHS) method to generate samples. The LHS method is widely used in building energy analysis as it can produce uniform and converging results with fewer samples [32,49,73]. In this study, the multi-level sampling framework was implemented using Python v3.8.8 with libraries such as Pandas v2.0.3 [75] and SciPy v1.10.1 [76]. The corresponding Python code is available in the open-source repository [50]. This code was used to generate a batch of samples, which were then exported as an Excel file. The exported samples were subsequently used in the simulation workflow to parametrically simulate each sample and report the outputs described in the previous section.

#### 3.3.2. Identifying appropriate sample size

The reliability of samples to represent the variations depends on

**Table 2**
Input data used for validating simulation workflow for terraced intermediate and apartment dwelling types [44].

| Input parameter | Terraced Intermediate | | | | Apartments | | | | Units |
|---|---|---|---|---|---|---|---|---|---|
| | <1945 | 1945–1975 | 1975–1995 | >1995 | <1945 | 1945–1975 | 1975–1995 | >1995 | |
| Orientation[1] | 0 | | | | 0 | | | | ° |
| Compactness-Ratio[1] | 1.2 | | | | 1.6 | 1.0 | 0.6 | 1.7 | – |
| Window-to-Wall Ratio[1] | 0.385 | | | | 0.417 | | | | – |
| Position of Apartment[2] | – | | | | I-R | C-I | I-I | C-G | – |
| Heated Floor Area[1] | 142 | | | | 64 | | | | m$^2$ |
| Ground Insulation, R | 0.77 | 0.57 | 1.16 | 2.68 | 0.56 | 0.48 | 1.16 | 2 | m$^2$·K/W |
| External Wall Insulation, R | 0.7 | 0.84 | 1.53 | 2.68 | 0.58 | 0.67 | 1.66 | 2.61 | m$^2$·K/W |
| Roof Insulation, R | 0.46 | 1.22 | 1.5 | 2.75 | 1 | 0.96 | 1.66 | 2.67 | m$^2$·K/W |
| Glazing Insulation, U | 2.96 | 2.73 | 2.82 | 2.1 | 3.11 | 2.87 | 2.91 | 2.16 | W/m$^2$·K |
| External Door Insulation, U | 3.36 | 3.31 | 3.33 | 3.27 | 3.32 | 3.30 | 3.32 | 3.28 | W/m$^2$·K |
| Infiltration[3] | 3 | 3 | 2.5 | 1.5 | 1.8 | 1.95 | 1.3 | 0.75 | dm$^3$/s.m$^2$ |
| Ventilation system | A | | C | | A | | C | | – |
| Heating setpoint[4] | 20/16 | | 20/18 | | 20/16 | | 20/18 | | °C |
| Space heating demand | 170 | 145 | 110 | 80 | 180 | 150 | 100 | 75 | kWh/m$^2$ |

[1]From the seed model.
[2]I-R: Intermediate-Roof, C-I: Corner-Intermediate, I-I: Intermediate-Intermediate and C-G: Corner-Ground.
[3]Calculated using equation (1).
[4]Living room and kitchen with 20 °C, bedrooms with 16 °C for dwellings built before 1975 and 18 °C for built after 1975.

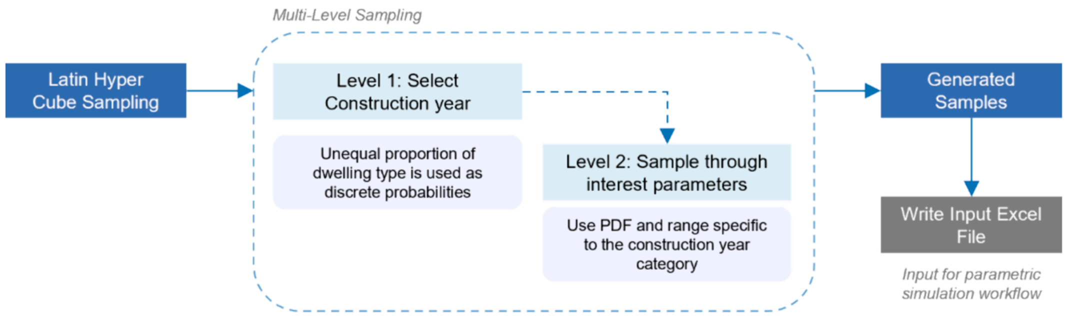


**Fig. 4.** Multi-level sampling scheme for generating representative samples for terraced-intermediate and apartment dwelling types.

selecting an appropriate sample size [32]. A comprehensive review by Pang et al. [49] on sensitivity analysis in building performance studies emphasises the importance of determining the right sample size to ensure reliable results while minimising computational costs. This review advocated assessing robustness and convergence over prior selection in order to determine sample size. Consequently, the present study employed GSA methods to identify the optimal sample size. The GSA approach allows for a thorough exploration of the entire input space by examining all possible combinations of input parameters, their interactions, and impacts on output parameters [71,77]. Additionally, these methods are categorised into screening-based, regression-based, variance decomposition and metamodel-based approaches [49,72,77,78]. This study utilised the SRRC method, a regression-based GSA technique. Compared to variance decomposition methods such as Sobol, SRRC can identify similar first-order interactions with fewer model evaluations, thus offering a computationally efficient alternative [72,79].

Further, the SRRC method was implemented as a post-processing step where it calculated the ranked regression coefficients for the two output parameters: space heating demand and underheated hours. The magnitude of the SRRC reveals the sensitivity of each parameter, while the sign indicates its positive or negative relationship with the output. Absolute coefficient values were used to rank the interest parameters for both outputs separately. In this study, the sample size was incrementally increased until the ranks and absolute SRRC values stabilised. At this point, it was indicated that the sample size was sufficiently representative of the possible variations within the dwelling type, and further increases would not significantly affect parameter sensitivities.

Additionally, the coefficient of determination ($R^2$) was used to gauge how well the interest parameters explained the variance in the output parameters within the regression model, while also serving as a measure of the model's linearity [49]. According to Saltelli, an $R^2$ value of 0.75 is considered acceptable for applying regression-based methods. If the $R^2$ is less than 0.75, rank-transformed methods such as SRRC are recommended [79]. Furthermore, SRRC and $R^2$ values were calculated using the Open TURNS v1.21 [80] library in Python.

### 3.4. Data processing and feature importance

#### 3.4.1. Radiator oversizing

Once the appropriate sample size has been determined, a new batch of samples is generated and simulated for the three supply temperatures: HT(90/70 °C), MT(70/50 °C) and LT(55/35 °C), following the procedures described in Sections 3.3 and 3.2, respectively. As outlined in Section 3.2.1.3, heating capacities are utilised to study the effects of different supply temperatures. This assumes that the design heat losses, calculated for the HT supply without any overcapacity, represent the design heating capacity of each zone. However, in practice, installed radiator capacity often exceeds these design capacities, commonly referred to as radiator oversizing. Radiators are frequently oversized due to safety margins applied by practitioners and assumptions made during the design stage. This oversizing might also result from renovations that reduce heat losses or from selecting a larger radiator size than is needed from what is available in the market [81–83]. A survey of 515 UK homes revealed that radiators are, on average, oversized by a factor of 1.46, although the degree of oversizing varies widely, impacting the adoption of LTH [82]. In the Netherlands, Pothof et al. [38] established a relationship between the design supply temperature and the inverse of the oversizing factor (defined in their study as dimensionless design heat output) based on a survey of 220 Dutch dwellings. Given an oversizing factor, this relationship can help determine the extent to which supply temperatures can be lowered without compromising occupant comfort.

Further, oversized radiators can affect the thermal comfort of a dwelling at lower temperatures. Therefore, it is crucial to consider oversizing when assessing the LTH readiness of the representative samples. Accordingly, this study assumes an additional heating capacity, often considered by practitioners as a safety margin, to heat the dwelling from cold temperatures after a period without heating. This extra capacity is calculated as 20 times the heated floor area of the thermal zone and added to its design heat losses (due to transmission and ventilation) to determine the installed heating capacity of the specific thermal zone [84]. It is important to note that while this assumption is applied generically across all samples, installed radiator capacity can be higher than this estimate due to the factors described above. The heating capacities calculated with this approach are applied at the HT level and adjusted for MT or LT, as outlined in Section 3.2.1.3.

#### 3.4.2. Labelling samples for LTH readiness

The simulated samples with assumed oversized heating capacity were evaluated using the LTH-ready definition described in Section 3.2.1.4. This evaluation aimed to label the samples as either "ready" or "not ready" for MT and LT supply. Fig. 5 illustrates this labelling process. Subsequently, the labelled datasets were analysed using a supervised machine learning technique, the Random Forest (RF) classification algorithm.

#### 3.4.3. Random forest classification

The RF algorithm is an ensemble-based machine-learning technique that addresses classification and regression problems by generating multiple decision trees during the training phase. Each tree is trained independently using different random samples generated through bootstrapping of the training data [39,85,86]. This algorithm is widely used in building performance studies due to its ability to handle high-dimensional data and various input types, such as categorical and continuous parameters [87]. Compared to other algorithms, RF models can provide good results without extensive hyperparameter tuning [88], and they allow for the extraction of feature importance, offering insights into the parameters that most influence the model's predictions [39].

Feature importance extraction from RF models has been utilised previously in studies focusing on energy performance and renovation for dwellings. For instance, Cheng and Ma [89] used the RF regression model to identify parameters influencing the energy performance of residential buildings in New York City. Their study investigated 171 features related to energy use intensity and identified the 20 most

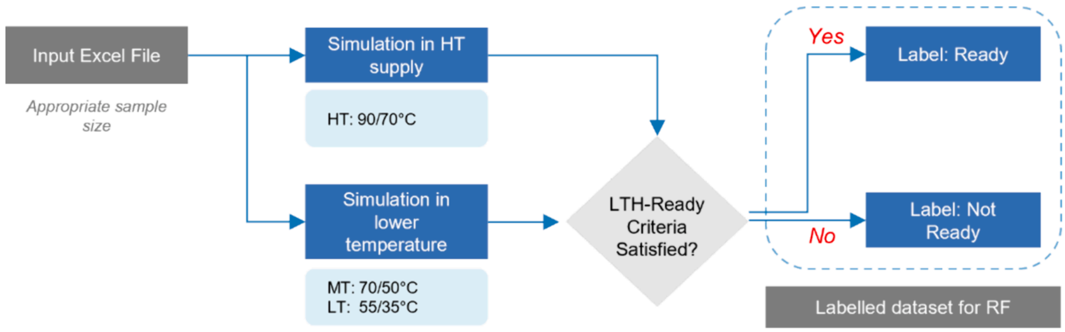


**Fig. 5.** Labelling process by applying LTH-ready criteria on MT and LT supply datasets. The labelled datasets were then used to train an RF classifier model.

influential parameters. Further, Olu-Ajayi et al. [90] employed an RF classifier model for feature selection from 23 input parameters. They selected the ten most impactful features for developing a machine learning regression model to forecast annual energy consumption in a large dataset of residential buildings. Additionally, Borragán et al. [91] utilised classification algorithms to identify renovation plans and their associated costs for different residential types in the Flemish region of Herentals. Through RF classification, their study extracted the relative importance of building features that are significant in predicting the type of renovation.

In this study, an RF classification model was trained on the labelled dataset for the terraced and apartment dwelling types (outlined in Section 3.4.2). Each dwelling type has two labelled datasets for MT and LT supply, resulting in a total of four RF classifier models. For model training, the features included interest parameters that caused variations within the dwelling type as well as affected their LTH readiness, with the readiness label serving as the target variable. A typical train-test split of 80:20 was used, where 80 % of the data was used for training the RF model, and the remaining 20 % was used for evaluating performance. The performance of the RF model was assessed using standard classification metrics such as accuracy, precision, recall and F1 scores [39,43,91,92]. These metrics provide various measures of model performance concerning correct predictions (True Positives and True Negatives) and classification errors (False Positives and False Negatives).

In the context of this study, True Positives and True Negatives represent the number of samples correctly predicted as “ready” or “not ready”, respectively, for a particular lower supply temperature. False Positives are samples incorrectly predicted as “ready” when they are not, while False Negatives are samples predicted as “not ready” when they actually are. Accuracy measures the overall correctness of the model in predicting LTH readiness. Meanwhile, precision measures the proportion of samples predicted as “ready” that were actually “ready,” with high precision indicating that the model’s “ready” predictions are usually correct. Recall measures the model’s ability to identify actual “ready” samples among all the ready samples, with high recall indicating that the model effectively captures most “ready” instances. Lastly, F1 scores provide a single metric that balances precision and recall.

After evaluating model performances, the feature importances for each dwelling type at both supply temperature levels were extracted. The relative importance of each parameter was examined to understand its contribution to the model’s predictions. This analysis provided a clear understanding of which building-level parameters are most influential in determining the readiness of each dwelling type for both MT and LT supply. Additionally, the analysis accounted for variations due to these parameters, offering a comprehensive view of their effects.

## 4. Results

### 4.1. Validation of the parametric simulation workflow

The parametric workflow was validated by generating and simulating models using the input data described in Table 2, derived from [44]. For validation, the model generation adhered to the assumption in [44] that the design heating capacities are equivalent to the design heat losses without oversizing. These calculated heating capacities for the thermal zones were considered for the HT supply. Fig. 6 illustrates the validation results, comparing the benchmark and simulated space heating demand for terraced-intermediate houses and apartments across each construction category. Additionally, the position of the apartment indicates the effect of location. The graph demonstrates that, given the input data from Table 2, the models generated through the workflow can simulate within a 20 % deviation from the benchmark performance. However, variations exist where the models either overestimate or underestimate the performance. These discrepancies are attributed to differences in assumptions and calculation methods. For instance, the benchmarks provided by [44] were calculated using NTA8800, which employs steady-state calculation with correction factors, whereas this study utilised dynamic simulation.

### 4.2. Determining the appropriate sample size

The validated simulation workflow was used to determine the appropriate sample size for both dwelling types. The simulated data from each sample size iteration was post-processed using the SRRC method to assess the sensitivity of the input parameters to the output parameters, specifically space heating demand and underheated hours. Additionally, the sample size was iteratively increased in multiples of 100 until the ranks and SRRC values stabilised, representing the appropriate sample size to capture variations in the dwelling type. This process was conducted separately for each dwelling type and the two supply temperatures (MT and LT).

Figs. 7 and 8 illustrate the parameter ranking, absolute SRRC, and the $R^2$ values for the two output parameters for terraced-intermediate and apartment dwellings, respectively, under the MT supply of 70/50 °C. The SRRC ranks and absolute values were analysed together, as the ranks are sensitive to slight changes in the absolute SRRC values. For the terraced dwellings (Fig. 7), the SRRC ranks for many parameters stabilised at 1000 samples for space heating demand. In contrast, for underheated hours, the ranks stabilised after 1200 samples. The sample size with comparatively higher $R^2$ for both outputs was chosen as it can better explain the variance in them. Therefore, a sample size of 1300 was selected.

A similar process was applied to the apartment dwelling type. Fig. 8 shows that stabilisation of the ranks and SRRC values for many parameters were achieved at 1000 samples for space heating demand and 700 for underheated hours. Compared to the terraced-intermediate type, the apartment dwelling type exhibited a lower $R^2$ value, indicating

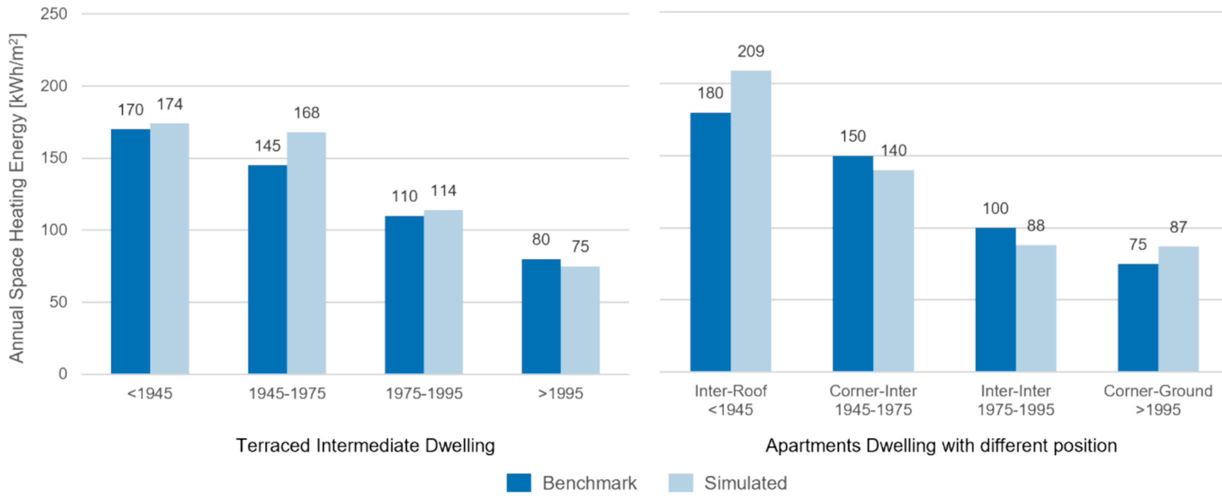


**Fig. 6.** Validation of the parametric simulation workflow by comparing benchmark data from [44] with simulated model performance.

higher non-linear effects, thereby justifying the use of the SRRC method. Nevertheless, the sample size with the highest $R^2$ again corresponded to 1300 samples. The same experiment was repeated with the LT supply, varying the sample size between 1000 and 1400, as shown in Figures E.1 and E.2 in Appendix E. It was found that for LT supply, the ranking, absolute SRRC, and $R^2$ values also converged at a sample size of 1300. Thus, it was concluded that a sample size of 1300 for terraced-intermediate and apartment types is appropriate for representing the variations due to the interest parameters within the dwelling types.

### 4.3. Labelling for LTH-Readiness of dwelling types

A new batch of 1300 samples was generated and subjected to annual simulations under HT, MT and LT supply. The generic assumption of radiator oversizing (outlined in Section 3.4.1) was considered when calculating the design heating capacities under HT supply. The dataset with simulated outputs was labelled for LTH-readiness as described in Section 3.4.2. Further, Fig. 9 illustrates the distribution of terrace-intermediate and apartment types being LTH-ready under MT and LT supply.

The graph illustrates that, in the current state, approximately 14 % of terraced-intermediate samples are ready to be heated with DH systems under MT supply. In contrast, 71 % of apartment dwellings are suitable for MT supply. However, neither the apartment nor terraced-intermediate type is prepared for LT supply from DH systems. Specifically, only one terraced-intermediate sample was ready for LT supply, compared to 18 apartment samples. This indicates that the majority of terraced-intermediate dwelling types are not yet suitable for either MT or LT supply and would require energy renovations before being connected to DH systems under these temperature supply conditions. While apartment dwellings show significant readiness for MT supply, they nevertheless need adjustments to be suitable for LT supply from DH systems.

The LTH-readiness assessment was conducted on samples generated from various combinations of interest parameters, reflecting the diversity within each dwelling type. Given these findings, it is essential to identify the significance of interest parameters in determining the readiness of the dwelling types for MT and LT supply. The study argues that understanding the importance of these parameters could provide robust insights. In addition, such insights can subsequently inform and help prioritise renovation measures to prepare dwellings for LTH when supplied by DH systems.

### 4.4. Classification models and feature importance

#### 4.4.1. Data processing for model training

The RF classifier was utilised to train the models on the labelled datasets to predict the readiness of samples for both dwelling types for MT and LT supply. From these classification models, the relative importance of the features (interest parameters) used to predict the target variable (LTH-readiness label) was extracted. This ranking of feature importance aids in identifying the parameters that influence the readiness of the dwellings. However, as shown in Fig. 9, the labelled dataset exhibits a significant class imbalance problem.

Class imbalance refers to datasets with an unequal proportion of positive and negative classes [93,94]. This issue is commonly observed in scenarios such as fraud detection or medical diagnosis, where most of the instances correspond to the negative class (referred to as the majority class) compared to the positive class (referred to as the minority class) [93,95]. The class imbalance problem impacts classification accuracy and can introduce bias into the trained model. Therefore, it is essential to address the imbalance in the dataset prior to using it for model training. One approach suggested in the literature is cost-sensitive learning, which assigns a higher cost to misclassifying the minority class during training [94,95]. This study implemented the class weighting using the built-in functionality of the RF classifier available in the Scikit-learn v1.4.2 Python library [96].

Moreover, the RF models for terrace-intermediate and apartment dwelling types were trained for MT supply by assigning weights to the respective minority and majority classes. In contrast, for both dwelling types, very few samples are ready under LT supply; thus, the data is deemed insufficient for training the models for it. As per the LTH ready criteria, a sample is considered ready if the space heating demand and underheated hours in the lower temperature supply are less than or equal to those in the HT supply. Specifically, for underheated hours, this means that a sample under LTH with even one more underheated hour than that of HT supply would be considered not ready for the lower supply temperature. This strict criterion might be too rigid in reality and requires an experimental investigation of the acceptable range of discomfort hours for a dwelling to be ready for LTH. Consequently, a necessary assumption was made to relax the underheated hours criterion by 15 h for both dwelling types under LT supply conditions. These hours represent one occupied day in the living room between 8:00–23:00. The relaxed criteria resulted in 8 % of terraced-intermediate and 33 % of the apartment samples being ready for LT supply, which can now be used for training RF models with class-weighting.

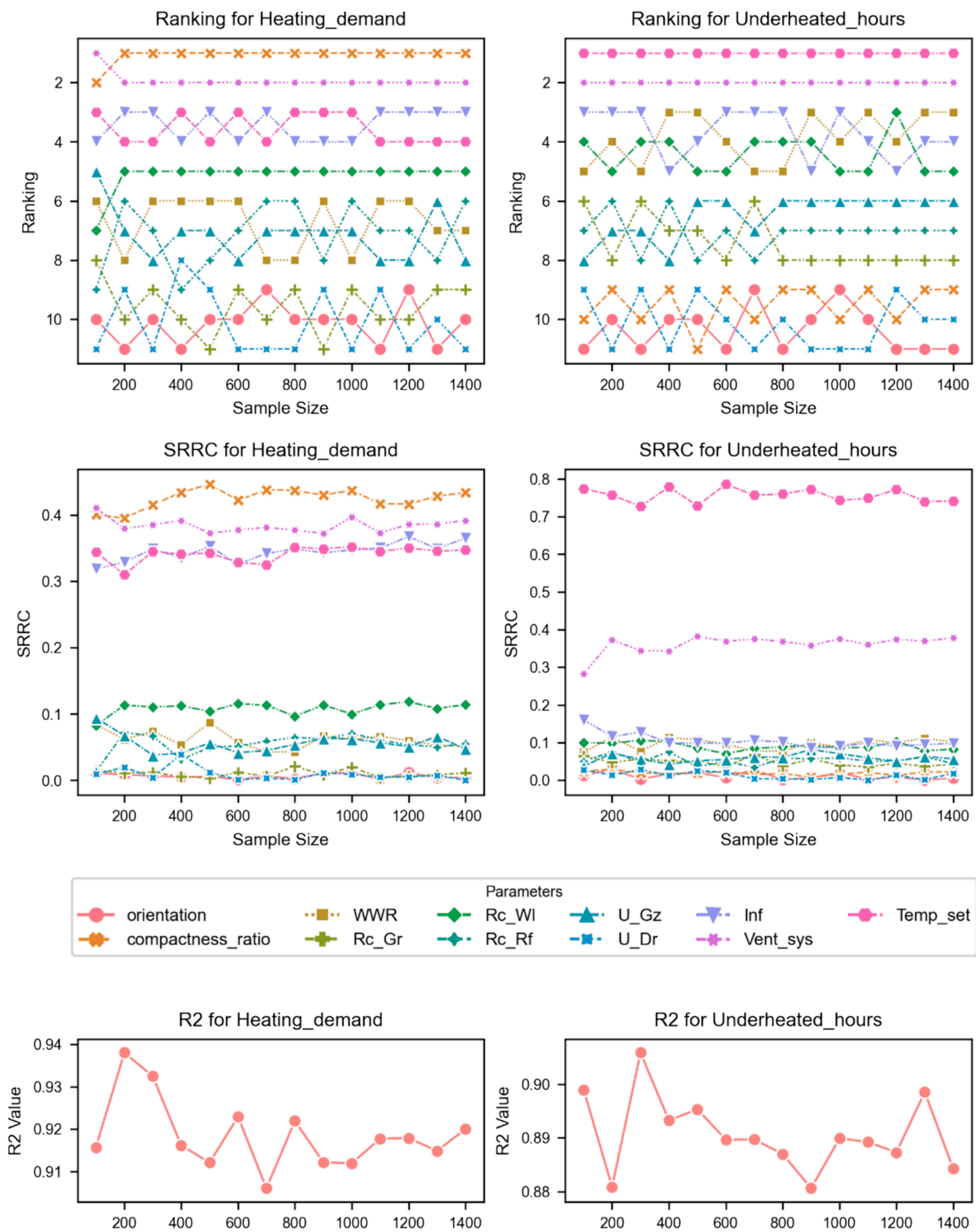


**Fig. 7.** Parameter ranking, SRRC absolute and $R^2$ values of terraced-intermediate dwelling type for the two output parameters under MT supply of 70/50 °C.

#### 4.4.2. *Evaluation of trained models*

Two training scenarios were employed to compare model performance: one using the original imbalanced dataset and the other using the cost-sensitive approach. The trained models were then evaluated using the test dataset, which was kept aside during the training phase. Despite the different training methods, the class distribution remained imbalanced. Therefore, balanced accuracy, which measures the average accuracy of the model for both minority and majority classes, was used. Additionally, precision, recall, and F1 scores were considered to evaluate the models' performance. Table 3 shows the performance of the trained models on the test dataset for two supply temperatures for terraced-intermediate and apartment dwelling types. The Table also compares the models trained for each supply temperature using the original imbalanced dataset and the cost-sensitive approach.

The RF model is preferred for terraced-intermediate dwellings under MT supply due to its higher balanced accuracy and recall score, despite the RF_weighted model exhibiting slightly better precision. This implies that the RF model is more effective at correctly identifying both "ready" and "not ready" cases, thus providing a robust assessment of readiness. However, it may generate a few false positives when compared to the RF_weighted model due to its slightly lower precision. The higher recall ensures that most dwellings that are actually ready for MT supply are correctly identified. Conversely, the RF_weighted model is favoured under LT supply due to its better balance between Precision and Recall, resulting in a higher F1 Score. This suggests that the RF_weighted model can more accurately identify actual ready cases while minimising false positives, leading to more reliable readiness predictions.

Further, for apartments, the RF_weighted model consistently outperforms the RF model. Under MT supply, the RF_weighted model shows higher balanced accuracy and precision. It is important to note that the

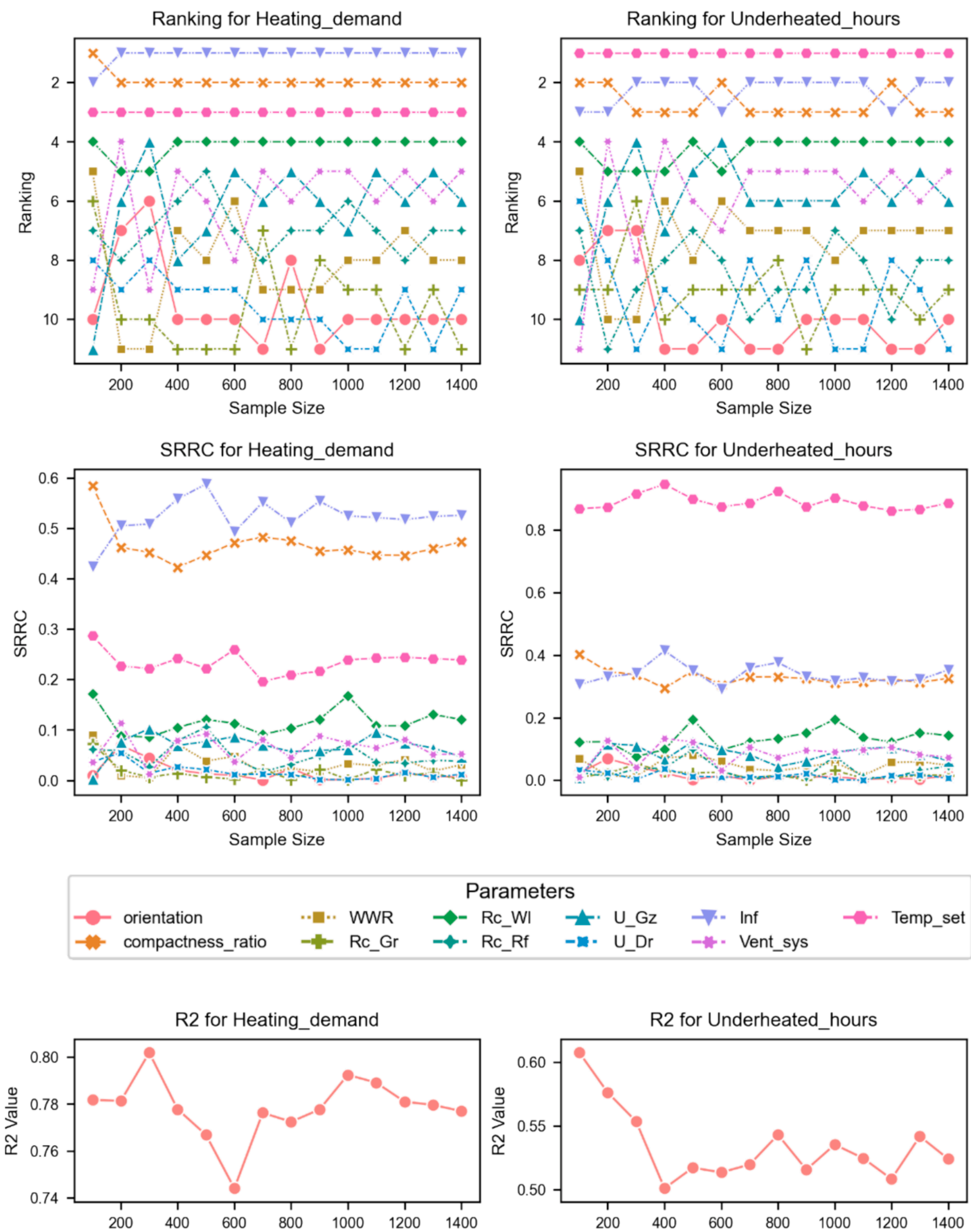


**Fig. 8.** Parameter ranking, SRRC absolute and $R^2$ values of apartment dwelling type for the two output parameters under MT supply of 70/50 °C.

minority class in this model is the negative class. Therefore, the precision and recall scores reflect the model's performance in predicting the "not ready" class. Even though the RF_weighted model surpasses the RF model in these metrics, its overall performance is lower than other models, suggesting the need for further hyperparameter tuning. Lastly, the RF_weighted model performs better across all metrics for apartments under LT supply, effectively identifying both "ready" and "not ready" cases.

### 4.4.3. *Extracted feature importance*

The relative importance of the features is presented in Table 4 in descending order of their contribution to the model's predictions for MT and LT supply in terraced-intermediate and apartment dwelling types, respectively. The Table highlights that building-level features affect the readiness differently for each dwelling type. Regarding specific supply temperatures, the parameters influencing readiness for MT and LT in terraced-intermediate types are similar, with some fluctuations. In contrast, feature importance rankings for apartments show variations, as detailed in Table 4. However, some general trends can be observed for the parameters affecting readiness for LTH in both dwelling types.

For instance, the heating setpoint is among the most influential parameters for both dwelling types, contributing 20–50 % in the prediction of a sample's readiness for LTH. A lower heating setpoint could reduce space heating energy, although it might increase the number of underheated hours. Even though a higher temperature setpoint for heating could reduce uncomfortable hours due to underheating, it could increase space heating energy consumption. This highlights the crucial role of occupants and their heating preferences in dictating the readiness

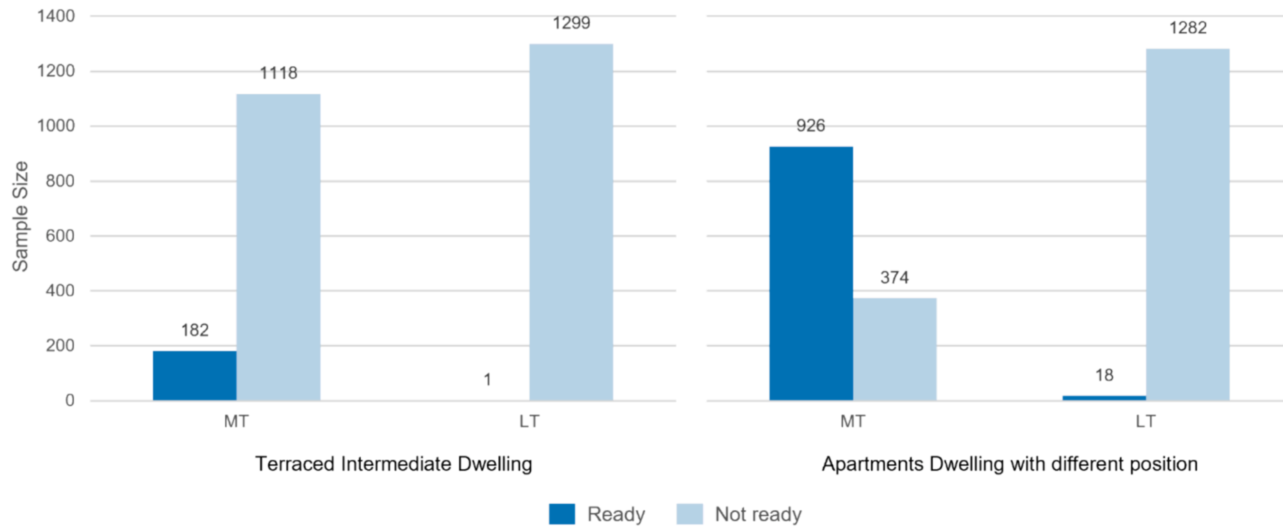


**Fig. 9.** Distribution of LTH-readiness of terraced-intermediate and apartment dwelling types for MT and LT supply.

**Table 3**
Evaluation of the trained classification models on the test set. The models were trained using the original imbalanced dataset (RF) and cost-sensitive approach (RF_weighted) for MT and LT supply for both dwelling types.

| Evaluation metrics | Terraced-Intermediate | | | | Apartment | | | |
|---|---|---|---|---|---|---|---|---|
| | MT supply | | LT supply* | | MT supply | | LT supply* | |
| | RF | RF_weighted | RF | RF_weighted | RF | RF_weighted | RF | RF_weighted |
| Balanced Accuracy | 0.892 | 0.851 | 0.962 | 0.951 | 0.774 | 0.782 | 0.922 | 0.928 |
| Precision | 0.902 | 0.916 | 0.741 | 0.880 | 0.800 | 0.842 | 0.897 | 0.898 |
| Recall | 0.804 | 0.717 | 0.958 | 0.916 | 0.615 | 0.615 | 0.897 | 0.909 |
| F1 Score | 0.850 | 0.804 | 0.836 | 0.897 | 0.695 | 0.711 | 0.897 | 0.903 |

*Model trained on relaxed underheated hours criteria.

**Table 4**
Importance Ranking for terraced-intermediate and apartment dwelling type for readiness in MT and LT supply. The numbers represent the contribution of features in predicting LTH readiness.

| Rank | Terraced-Intermediate | | | | Apartment | | | |
|---|---|---|---|---|---|---|---|---|
| | MT | | LT | | MT | | LT | |
| 1 | Heating Setpoint | 0.326 | Heating Setpoint | 0.558 | Infiltration | 0.238 | Heating Setpoint | 0.465 |
| 2 | Ventilation System | 0.217 | Ventilation System | 0.228 | Compactness-Ratio | 0.174 | Infiltration | 0.250 |
| 3 | Roof Insulation | 0.062 | Roof Insulation | 0.035 | Heating Setpoint | 0.119 | Roof Insulation | 0.048 |
| 4 | Glazing Insulation | 0.059 | Infiltration | 0.032 | External Wall Insulation | 0.087 | Compactness-Ratio | 0.043 |
| 5 | Infiltration | 0.057 | Glazing Insulation | 0.031 | Glazing Insulation | 0.081 | Ventilation System | 0.040 |
| 6 | Orientation | 0.055 | Orientation | 0.028 | Roof Insulation | 0.075 | Glazing Insulation | 0.040 |
| 7 | External Wall Insulation | 0.053 | External Wall Insulation | 0.023 | Ground Insulation | 0.070 | External Wall Insulation | 0.034 |
| 8 | Compactness-Ratio | 0.051 | External Door Insulation | 0.019 | External Door Insulation | 0.058 | Ground Insulation | 0.029 |
| 9 | Ground Insulation | 0.050 | Ground Insulation | 0.018 | Ventilation System | 0.045 | External Door Insulation | 0.025 |
| 10 | External Door Insulation | 0.042 | Compactness-Ratio | 0.013 | Orientation | 0.032 | Orientation | 0.011 |
| 11 | Window-to-Wall Ratio | 0.022 | Window-to-Wall Ratio | 0.011 | Window-to-Wall Ratio | 0.016 | Window-to-Wall Ratio | 0.010 |

of the dwelling.

Following the heating setpoint, the parameters related to the ventilation heat losses significantly influence LTH readiness. Overall, it can be seen that ventilation systems are more impactful for terraced-intermediate dwellings, whereas, for apartments, infiltration is more influential. These findings align with other studies exploring the influential features affecting the prediction of heating demand from machine learning models. Ali et al. [43] trained a machine learning model to predict the energy performance of the Irish building stock and found that the most influential characteristics for heating demand are air change rate and temperature setpoints for heating, followed by fabric-related parameters. Similarly, Álvarez-Sanz et al. [27] identified infiltration as an influential parameter in space heating demand using machine learning algorithms. These results indicate the importance of curbing ventilation heat losses with efficient ventilation systems and reducing the infiltration rate to prepare the dwelling types for heating with lower supply temperatures.

In terms of building envelope insulation, except for apartments in MT supply, the dwelling types follow a similar pattern of influence. Roof and window insulations are the most influential, followed by wall insulation, with ground insulation and door insulation being consistently less influential. This aligns with the study by Borragán et al. [91], who trained a random forest classifier model to predict renovation measures for different dwellings in the Flemish region of Herentals, Belgium. They also found that roof insulation had the highest influence, followed by window, wall, and ground-floor insulation.

Regarding geometric properties, the window-to-wall ratio does not significantly influence LTH readiness for either dwelling type. A possible reason could be the lack of variations during the sampling process. The window-to-wall ratio variable was fixed with the average ratio for each construction year and for both dwelling types, as per [45]. Compared to the terraced-intermediate type, the compactness ratio has a more substantial influence on apartments, as it also considers the dwelling's position, which determines the heat loss area and affects LTH readiness. Lastly, orientation is shown to have some effect on terraced dwellings but a minimal influence on apartments.

### *4.5. Effect of radiator oversizing on LTH readiness*

As described in Section 3.4.1, radiator oversizing might influence the readiness of dwellings for LTH. To investigate this, a separate analysis was conducted. The oversizing factor is calculated as the ratio of installed heating capacity to design heating output. In this study, the design heating output is determined by the steady-state heat loss under design conditions. However, the installed heating capacity can vary for each dwelling, making it difficult to determine without an on-site inspection. Nevertheless, a recent study by Pothof et al. [38] provides insight into oversizing factors based on surveying and monitoring 220 dwellings representative of existing Dutch homes. Their study found that the oversizing factor ranges between 1.25 and 5 for the sample studied, varying with the dwelling types.

To assess the impact of the radiator oversizing on LTH suitability, four oversizing factors (1.25, 1.66, 2.5, 5) were used. The results were compared with the generic oversizing assumption described in Section 3.4.1. A batch of 1300 samples was simulated under HT, MT, and LT supply conditions, incorporating these four oversizing factors. Further, these samples were evaluated using the LTH readiness definition to determine the increase in readiness for different oversizing factors.

Furthermore, Fig. 10 illustrates the effect of oversizing factors on the readiness of terraced-intermediate and apartment dwelling types for LTH. The Figure shows that a higher oversizing factor generally corresponds to a higher level of readiness for lower temperature supply. Additionally, different oversizing factors indicate varying degrees of readiness, with apartments typically being more prepared for MT and LT supply. For terraced-intermediate dwellings, an oversizing factor in the range of 2.5 to 5 is required for over 50 % of the samples to be ready for MT or LT supply. In contrast, apartments require a lower oversizing factor, between 1.25 and 2.5, to be prepared for LT supply, as they are already ready for MT supply. These results complement the findings by Pothof et al. [38], suggesting that the oversizing factor is a significant parameter influencing LTH readiness. However, it is essential to investigate the uncertainties associated with the oversizing factor by incorporating data on installed heating capacity in national housing surveys.

## 5. Discussion

### *5.1. Sampling-based approach*

This study identified the most influential factors affecting the LTH readiness of terraced-intermediate and apartment dwelling types. Unlike the traditional archetype-based approach, a sampling-based method was adopted to incorporate the possible variations in dwelling types due to parameters that not only characterise a dwelling but may also affect LTH readiness. Further, the study determined that a sample size of 1300 for both dwelling types could represent the possible variations due to building-level interest parameters. While a larger sample size can reduce uncertainties caused by variations in dwelling types, the determination of the sample size depends on the study's context, interest parameters, and available computational resources. Therefore, this determination must be made for each specific study and should not be generalised.

Currently, the study was limited to terraced-intermediate and apartment dwelling types, although the sampling-based method can be scaled to include other dwelling types, such as detached and semi-detached. Additionally, the multi-level sampling framework can be adjusted to sample through the entire building stock, thus providing opportunities to adapt the approach from the building to the dwelling stock level. However, a potential bottleneck in the methodology corresponds to the iterative generation of HBjson models from the parametric simulation workflow in the Grasshopper environment. The time taken to generate the Hbjson depends on the processing capacity of the local system, which directly affects the number of samples that could be studied. A possible solution would be to develop the simulation workflow through custom scripts on Python. This can be achieved by exploiting libraries such as Geomeppy to alter the geometrical aspects of the samples and Eppy for EnergyPlus simulations.

### *5.2. Implications of feature importance*

Extracting feature importances from the trained models offers valuable insights into the factors influencing the model's predictions. These insights help to create an understanding of the key parameters determining the readiness of dwellings for LTH. According to Table 4, both dwelling types have different parameters affecting their readiness. However, there are some commonalities across both types.

In general, the findings of this study suggest that parameters related

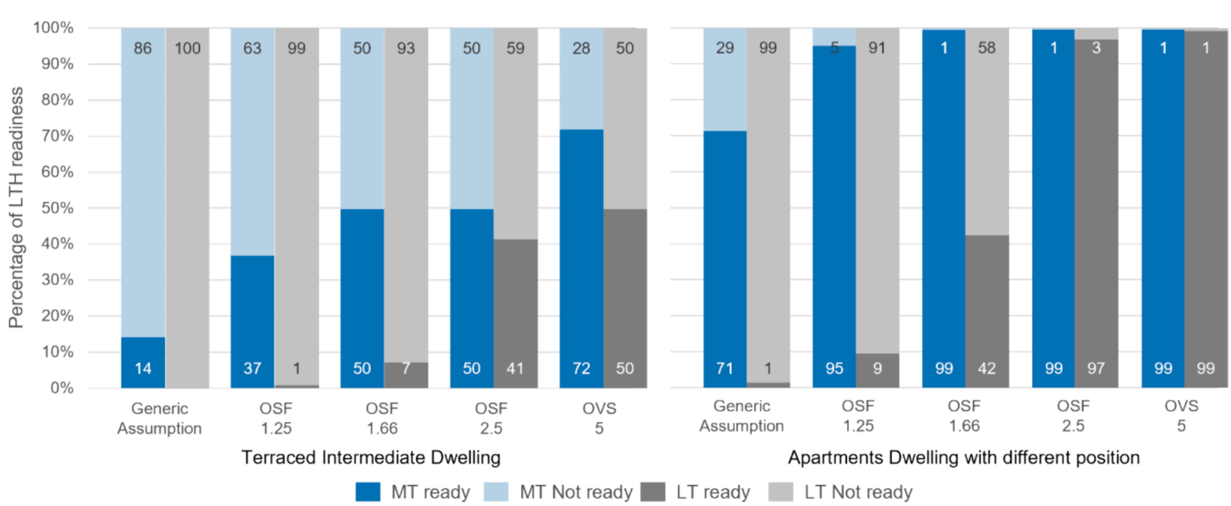


**Fig. 10.** The effect of different oversizing factors on the LTH readiness of the dwelling types.

to occupancy have the most significant influence on a dwelling's readiness for LTH. This is followed by the impact of HVAC systems, building envelope insulation, and geometric properties. While these findings can be generalised to some extent at the dwelling stock level, they also reveal the specific impacts of different building-level parameters for each dwelling type. Therefore, to accurately assess a dwelling's readiness for LTH, it is essential to consider the relative importance identified for the particular dwelling type. However, it should be noted that these results are based on the specific data and variables studied. Incorporating additional variables and improvements in the data generation method can refine the importance rankings and enhance the overall analysis. In addition to these parameter influences, radiator oversizing has a significant impact on the readiness of the dwelling. Future studies should include this factor, along with associated uncertainties, for a more comprehensive analysis of LTH readiness in the Netherlands.

Regarding the practical implications, the influence of building-level parameters can guide the prioritisation of renovation measures to make dwellings LTH-ready. The selection of appropriate renovation measures would be based on additional decision-making criteria, such as carbon emissions, initial investment, life cycle cost, payback period, and hassle for the occupants. Nevertheless, the feature importance can be used to prioritise renovation strategies in order to develop targeted measures to make the dwelling LTH-ready. This can significantly help stakeholders to reduce decision-making struggles by alleviating the decision paralysis that occurs when selecting appropriate solutions from various available renovation options.

## 6. Conclusions

Transitioning existing dwellings in the Netherlands to lower-temperature heating (LTH) supplied by district heating (DH) is essential for achieving the Dutch decarbonisation goals. Consequently, energy renovations might be required to prepare them to be heated with LTH. However, the heterogeneity of the housing stock poses significant challenges in determining the necessary energy renovations and selecting appropriate strategies. To address these challenges, this study provides a comprehensive assessment of building-level parameters that affect the readiness of Dutch dwellings, particularly terrace-intermediate and apartment dwelling types, for LTH from the DH system. By employing a sampling-based approach, representative samples were generated to capture the inherent variability within these dwelling types. This method addresses the limitations of traditional archetype-based approaches by incorporating a broader range of building-level parameters and variations, thereby offering a more robust framework for evaluating LTH readiness.

The findings revealed that a sample size of 1300 is adequate to incorporate the variations within the terraced-intermediate and apartment dwelling types. These samples were assessed for LTH readiness by comparing them to high-temperature (HT: 90/70 °C) supply benchmarks and evaluating their suitability for medium-temperature (MT: 70/50 °C) and low-temperature (LT: 55/35 °C) supply. The results indicate significant differences in the readiness of these dwelling types for lower temperature supply conditions. Specifically, terraced-intermediate dwellings show limited readiness for both MT and LT supply. Conversely, while a considerable proportion of apartment dwellings are ready for MT supply, very few are suitable for LT supply, highlighting the varying levels of LTH readiness.

Moreover, the feature importance analysis from the Random Forest (RF) classification models underscores the critical influence of building-level parameters. Key factors influencing LTH readiness include (in this order of importance) temperature setpoints for heating, ventilation-related parameters (ventilation system and infiltration), fabric-related parameters (roof, glazing, wall, ground, and door insulation), and geometric properties (orientation, compactness ratio, and window-to-wall ratio). To accurately assess a dwelling's readiness for LTH, it is crucial to consider the relative importance of these factors specific to the dwelling type. Additionally, radiator oversizing significantly impacts LTH readiness, suggesting that future studies should incorporate this factor and its associated uncertainties for a more comprehensive analysis of LTH readiness in the Netherlands.

These insights can guide stakeholders in inspecting the existing condition of the dwellings within their portfolio and prioritising renovation measures to make them LTH-ready. Understanding the influence of these parameters can help stakeholders develop targeted renovation measures, thereby reducing decision paralysis when selecting the appropriate renovation solutions. These findings are robust as they were derived by incorporating the representative variations within the studied dwelling types and can aid in preparing dwellings for LTH. However, it is essential to note that the results are based on the available data. Including more refined data could further improve the accuracy and nuance of the results, thereby better supporting the energy transition of the dwelling stock in the Netherlands.

## 7. Declaration of generative AI in scientific writing

During the preparation of this work, the authors used ChatGPT and Grammarly to improve the clarity and cohesion of the text. After using this tool/service, the authors reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

## CRediT authorship contribution statement

**Prateek Wahi:** Writing – review & editing, Writing – original draft, Software, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Thaleia Konstantinou:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization. **Henk Visscher:** Writing – review & editing, Funding acquisition, Conceptualization. **Martin J. Tenpierik:** Writing – review & editing, Supervision, Methodology, 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

The dataset and corresponding code are available on 4TU. ResearchData and can be accessed through the following DOI: https://doi.org/10.4121/65afe08d-ee21-4531-9218-5f595cef7f69.v1.


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## Appendix A:. Detailed process workflow

Figure A.1 illustrates the detailed process followed in this study.

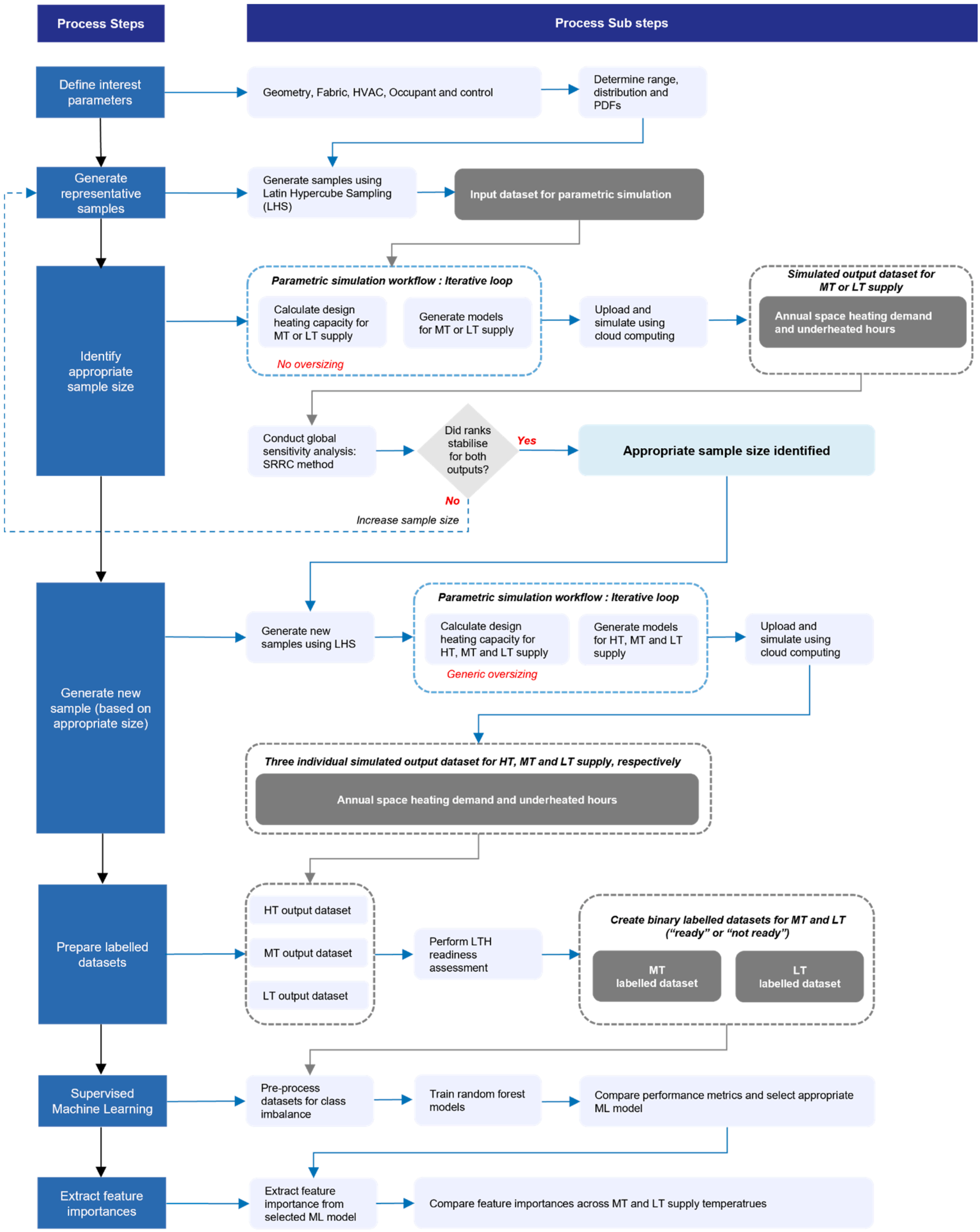


**Fig. A1.** Detailed process steps and sub-steps followed in this study.

## ' B:. Typical dwelling layouts

Figure B.1 presents the typical layouts for terraced-intermediate [51,52] and apartment dwelling types [55]. For terraced-intermediate dwellings, an overall height of 10.6 m and a floor-to-floor height of 2.7 m are considered. In contrast, a floor-to-floor height of 2.8 m is used for apartment dwellings.


**Fig. B1.** Typical dwelling layouts for terraced-intermediate and apartments [51,52,55].

## Appendix C:. Geometrical relationship between length and compactness ratio

***Terraced-Intermediate***

The sampling procedure developed utilises the probabilities specified in Tables D.2–D.5 to sample the compactness ratio (CR) for terraced-intermediate dwelling types. To represent the sampled CR, the seed model is scaled along its length while maintaining a fixed width of 5.4 m and a height of 10.6 m. Consequently, a geometrical relationship is established to calculate the new length (L) for the sampled CR, described in Equation (C.1).

$$CR = \frac{3.89{*}L + 61.56 + 10.8\sqrt{24.01 + \left(\frac{L}{2}\right)^2}}{14.58{*}L} \tag{C1}$$

According to Kafaei [97] and Esposito et al. [98], the length of a terraced dwelling typically ranges from 5 to 15 m. Applying this range in Equation (C.1) results in a compactness ratio between 0.99 and 1.9. These values align with the probabilities of the compactness ratio found in Tables D.2–D.5, where higher probabilities correspond to a range of 1.0 to 2.0. However, houses built before 1975 may exhibit a compactness ratio exceeding 2.0. For the purposes of this study, a length range of 5 to 15 m is used as a constraint. This constraint is applied during the sampling process, where the sampler first determines the compactness ratio and then calculates the length using Equation (C.1). If the length falls within the 5 to 15 m range, the sample is retained in the batch for further evaluation. This approach ensures that only relevant samples are included in the analysis.

***Apartments***

The sampling procedure for apartments also utilises the probabilities outlined in Tables D.7–D.10 for different construction years. Similar to the terraced-intermediate type, a relationship is established between the compactness ratio (CR) and the length (L) of the apartment, with a fixed width of 6.74 m and a height of 2.8 m. However, individual apartments differ in their position within the apartment block, which impacts their external heat loss area. Consequently, the compactness ratio is calculated for six typical positions. Table C.1 illustrates the geometrical relationship between CR and L for each position, with conditions to avoid division by zero. For apartment types, to ensure realistic sampling, length limits were derived based on the average floor area for MFH types from the reference home study [45]. According to this study, the usable heated area for MFHs ranges from 25 to 150 $m^2$. Given the fixed width of 6.74 m for the apartments, this corresponds to a length limit ranging from 3.7 to 22 m.

**Table C1**
Specific geometric relationship between compactness ratio and length of the apartment for each position. The conditions ensure avoiding division by zero.

| Position | Description | Relationship | Condition |
|---|---|---|---|
| 1 | Intermediate-Intermediate | $L = \frac{5.6}{CR}$ | $CR > 0$ |
| 2 | Corner–Intermediate | $L = \frac{5.6}{CR - 0.415}$ | $CR > 0.415$ |
| 3 | Intermediate – Ground | $L = \frac{5.6}{CR - 0.7}$ | $CR > 0.7$ |
| 4 | Intermediate – Roof | $L = \frac{5.6}{CR - 1}$ | $CR > 1$ |
| 5 | Corner – Ground | $L = \frac{5.6}{CR1.15}$ | $CR > 1.15$ |
| 6 | Corner – Roof | $L = \frac{5.6}{CR - 1.415}$ | $CR > 1.415$ |

## Appendix D:. Multi-Level sampling

### *Terraced-Intermediate*

Table D.1 shows the discrete probabilities for terraced-intermediate dwelling types across different construction year categories. These probabilities represent unequal proportions and are derived from [44]. The sampler first selects a construction year category based on these probabilities, which determines the probability density functions (PDFs) and ranges for the interest parameters. Tables D.2–D.5 illustrate the PDFs and parameter ranges for each construction year category.

**Table D1**
Discrete probabilities for construction year category for terraced-intermediate dwelling type [44].

| Parameter | Type | Distribution | Range | Probabilities |
|---|---|---|---|---|
| Construction Year | Discrete | Categorical | Until 1945 | 0.172 |
| | | | 1945–1975 | 0.309 |
| | | | 1975–1995 | 0.338 |
| | | | After 1995 | 0.181 |

**Table D2**
PDFs and Ranges for the interest parameters for the construction year category "until1945" for terraced-intermediate type.

| Category | Parameter | Type | Distribution | Range | Probabilities | Distribution* | Range* | Unit |
|---|---|---|---|---|---|---|---|---|
| Geometrical | Orientation | Discrete | Uniform | [0,45,90,135,180, 225, 270, 315] | – | – | – | ° |
| | Compactness Ratio[1] | Discrete | Categorical | 0.0–0.5 | 0.000 | Uniform | [0.0, 0.5) | – |
| | | | | 0.5–1.0 | 0.000 | | [0.5, 1.0) | |
| | | | | 1.0–1.5 | 0.412 | | [1.0, 1.5) | |
| | | | | 1.5–2.0 | 0.451 | | [1.5, 2.0) | |
| | | | | 2.0–2.5 | 0.113 | | [2.0, 2.5) | |
| | | | | 2.5–3.0 | 0.017 | | [2.5, 3.0) | |
| | | | | 3.0–3.5 | 0.008 | | [3.0, 3.5) | |
| | | | | 3.5–4.0 | 0.000 | | [3.5, 4.0) | |
| | Window–wall Ratio[2] | Discrete | Fixed | 31 | – | – | – | % |
| Fabric | Ground Insulation[2], R | Continuous | Triangle | [0.15, 5.04, 0.77] | Triangle PDF[3] | – | – | $m^2$·K/W |
| | External Wall Insulation[2], R | Continuous | Triangle | [0.19, 2.53, 0.7] | Triangle PDF[3] | – | – | $m^2$·K/W |
| | Roof Insulation[2], R | Continuous | Triangle | [0.22, 2.53, 1.24] | Triangle PDF[3] | – | – | $m^2$·K/W |
| | Window Insulaiton[2], U | Continous | Triangle | [1.4, 5.1, 2.96] | Triangle PDF[3] | – | – | W/$m^2$·K |
| | External Door Insulation[2], U | Continuous | Triangle | [2, 3.4, 3.36] | Triangle PDF[3] | – | – | W/$m^2$·K |
| | Infilteration[2] | Continuous | Triangle | [0.15, 5.04, 0.77] | Triangle PDF[3,4] | – | – | $dm^3$/s.$m^2$ |
| HVAC | Ventilation system[2] | Discrete | Categorical | [A, C, D] | [0.866, 0.129, 0.005] | – | – | – |
| Occupant and Control | Heating setpoint | Discrete | Uniform | [18–21] | – | – | – | °C |

* Sub-level data: After selecting a bin for the compactness ratio based on its probabilities, a value is sampled uniformly from the range of the chosen bin.
[1]Sourced from [45], [2] Sourced from [44], [3] Triangle distribution with [lower limit, upper limit, mode], [4] Calculated using equation (1) [56] in section 3.2.1.2.

**Table D3**
PDFs and Ranges for the interest parameters for the construction year category "1945-1975″ terraced-intermediate type.

| Category | Parameter | Type | Distribution | Range | Probabilities | Distribution* | Range* | Unit |
|---|---|---|---|---|---|---|---|---|
| Geometrical | Orientation | Discrete | Uniform | [0,45,90,135,180, 225, 270, 315] | – | – | – | ° |
| | Compactness Ratio[1] | Discrete | Categorical | 0.0–0.5 | 0.000 | Uniform | [0.0, 0.5) | – |
| | | | | 0.5–1.0 | 0.000 | | [0.5, 1.0) | |
| | | | | 1.0–1.5 | 0.582 | | [1.0, 1.5) | |
| | | | | 1.5–2.0 | 0.374 | | [1.5, 2.0) | |

(continued on next page)

**Table D3** (*continued*)

| Category | Parameter | Type | Distribution | Range | Probabilities | Distribution* | Range* | Unit |
|---|---|---|---|---|---|---|---|---|
| | | | | 2.0–2.5 | 0.042 | | [2.0, 2.5) | |
| | | | | 2.5–3.0 | 0.001 | | [2.5, 3.0) | |
| | | | | 3.0–3.5 | 0.001 | | [3.0, 3.5) | |
| | | | | 3.5–4.0 | 0.000 | | [3.5, 4.0) | |
| | Window–wall Ratio[2] | Discrete | Fixed | 36 | – | – | – | % |
| Fabric | Ground Insulation[2], R | Continuous | Triangle | [0.15, 5.48, 0.57] | Triangle PDF[3] | – | – | $m^2$·K/W |
| | External Wall Insulation[2], R | Continuous | Triangle | [0.19, 3.5, 0.84] | Triangle PDF[3] | – | – | $m^2$·K/W |
| | Roof Insulation[2], R | Continuous | Triangle | [0.22, 3.78, 1.22] | Triangle PDF[3] | – | – | $m^2$·K/W |
| | Window Insulaiton[2], U | Continous | Triangle | [1.56, 5.59, 2.73] | Triangle PDF[3] | – | – | W/$m^2$·K |
| | External Door Insulation[2], U | Continuous | Triangle | [2, 3.4, 3.31] | Triangle PDF[3] | – | – | W/$m^2$·K |
| | Infilteration[2] | Continuous | Triangle | [0.7, 3,3] | Triangle PDF[3,4] | – | – | $dm^3$/s. $m^2$ |
| HVAC | Ventilation system[2] | Discrete | Categorical | [A, C, D] | [0.791, 0.207, 0.002] | – | – | – |
| Occupant and Control | Heating setpoint | Discrete | Uniform | [18–21] | – | – | – | °C |

* Sub-level data: After selecting a bin for the compactness ratio based on its probabilities, a value is sampled uniformly from the range of the chosen bin.
[1]Sourced from [45], [2] Sourced from [44], [3] Triangle distribution with [lower limit, upper limit, mode], [4] Calculated using equation (1) [56] in section 3.2.1.2.

**Table D4**
PDFs and Ranges for the interest parameters for the construction year category "1975-1995" terraced-intermediate type.

| Category | Parameter | Type | Distribution | Range | Probabilities | Distribution* | Range* | Unit |
|---|---|---|---|---|---|---|---|---|
| Geometrical | Orientation | Discrete | Uniform | [0,45,90,135,180, 225, 270, 315] | – | – | – | ° |
| | Compactness Ratio[1] | Discrete | Categorical | 0.0–0.5 | 0.000 | Uniform | [0.0, 0.5) | – |
| | | | | 0.5–1.0 | 0.007 | | [0.5, 1.0) | |
| | | | | 1.0–1.5 | 0.697 | | [1.0, 1.5) | |
| | | | | 1.5–2.0 | 0.268 | | [1.5, 2.0) | |
| | | | | 2.0–2.5 | 0.028 | | [2.0, 2.5) | |
| | | | | 2.5–3.0 | 0.000 | | [2.5, 3.0) | |
| | | | | 3.0–3.5 | 0.000 | | [3.0, 3.5) | |
| | | | | 3.5–4.0 | 0.000 | | [3.5, 4.0) | |
| | Window–wall Ratio[2] | Discrete | Fixed | 31 | – | – | – | % |
| Fabric | Ground Insulation[2], R | Continuous | Triangle | [0.52, 5.38, 1.16] | Triangle PDF[3] | – | – | $m^2$·K/W |
| | External Wall Insulation[2], R | Continuous | Triangle | [0.8, 2.71, 1.53] | Triangle PDF[3] | – | – | $m^2$·K/W |
| | Roof Insulation[2], R | Continuous | Triangle | [0.44, 3.78, 1.5] | Triangle PDF[3] | – | – | $m^2$·K/W |
| | Window Insulaiton[2], U | Continous | Triangle | [1.8, 5.62, 2.82] | Triangle PDF[3] | – | – | W/$m^2$·K |
| | External Door Insulation[2], U | Continuous | Triangle | [2, 3.4, 3.33] | Triangle PDF[3] | – | – | W/$m^2$·K |
| | Infilteration[2] | Continuous | Triangle | [0.7, 2.5, 2] | Triangle PDF[3,4] | – | – | $dm^3$/s. $m^2$ |
| HVAC | Ventilation system[2] | Discrete | Categorical | [A, C, D] | [0.364, 0.621, 0.015] | – | – | – |
| Occupant and Control | Heating setpoint | Discrete | Uniform | [18–21] | – | – | – | °C |

* Sub-level data: After selecting a bin for the compactness ratio based on its probabilities, a value is sampled uniformly from the range of the chosen bin.
[1]Sourced from [45], [2] Sourced from [44], [3] Triangle distribution with [lower limit, upper limit, mode], [4] Calculated using equation (1) [56] in section 3.2.1.2.

**Table D5**
PDFs and Ranges for the interest parameters for the construction year category "after 1995" terraced-intermediate type.

| Category | Parameter | Type | Distribution | Range | Probabilities | Distribution* | Range* | Unit |
|---|---|---|---|---|---|---|---|---|
| Geometrical | Orientation | Discrete | Uniform | [0,45,90,135,180, 225, 270, 315] | – | – | – | ° |
| | Compactness Ratio[1] | Discrete | Categorical | 0.0–0.5 | 0.000 | Uniform | [0.0, 0.5) | – |
| | | | | 0.5–1.0 | 0.000 | | [0.5, 1.0) | |
| | | | | 1.0–1.5 | 0.658 | | [1.0, 1.5) | |
| | | | | 1.5–2.0 | 0.303 | | [1.5, 2.0) | |
| | | | | 2.0–2.5 | 0.032 | | [2.0, 2.5) | |
| | | | | 2.5–3.0 | 0.007 | | [2.5, 3.0) | |
| | | | | 3.0–3.5 | 0.000 | | [3.0, 3.5) | |
| | | | | 3.5–4.0 | 0.000 | | [3.5, 4.0) | |
| | Window–wall Ratio[2] | Discrete | Fixed | 29 | – | – | – | % |
| Fabric | Ground Insulation[2], R | Continuous | Triangle | [1.7, 6, 2.68] | Triangle PDF[3] | – | – | $m^2$·K/W |
| | External Wall Insulation[2], R | Continuous | Triangle | [1.51, 7, 2.68] | Triangle PDF[3] | – | – | $m^2$·K/W |
| | Roof Insulation[2], R | Continuous | Triangle | [2, 9, 2.75] | Triangle PDF[3] | – | – | $m^2$·K/W |
| | Window Insulaiton[2], U | Continous | Triangle | [1, 3.31, 2.1] | Triangle PDF[3] | – | – | W/$m^2$·K |
| | External Door Insulation[2], U | Continuous | Triangle | [1, 3.4, 3.27] | Triangle PDF[3] | – | – | W/$m^2$·K |
| | Infilteration[2] | Continuous | Triangle | [0.7, 1.5, 1] | Triangle PDF[3,4] | – | – | $dm^3$/s.$m^2$ |
| HVAC | Ventilation system[2] | Discrete | Categorical | [A, C, D] | [0.005, 0.832, 0.163] | – | – | – |
| Occupant and Control | Heating setpoint | Discrete | Uniform | [18–21] | – | – | – | °C |

* Sub-level data: After selecting a bin for the compactness ratio based on its probabilities, a value is sampled uniformly from the range of the chosen bin.
[1]Sourced from [45], [2] Sourced from [44], [3] Triangle distribution with [lower limit, upper limit, mode], [4] Calculated using equation (1) [56] in section 3.2.1.2.

***Apartments***

Table D.6 shows the discrete probabilities for apartment dwelling types across different construction year categories. These probabilities represent unequal proportions and are derived from [44]. The sampler first selects a construction year category based on these probabilities, which determines the probability density functions (PDFs) and ranges for the interest parameters. Tables D.7–D.10 illustrate the PDFs and parameter ranges for each construction year category.

**Table D6**
Discrete probabilities for construction year category for apartment dwelling type [44].

| Parameter | Type | Distribution | Range | Probabilities |
|---|---|---|---|---|
| Construction Year | Discrete | Categorical | Until 1945 | 0.1870 |
| | | | 1945–1975 | 0.3004 |
| | | | 1975–1995 | 0.2464 |
| | | | After 1995 | 0.2662 |

**Table D7**
PDFs and Ranges for the interest parameters for the construction year category "until 1945″ apartment type.

| Category | Parameter | Type | Distribution | Range | Probabilities | Distribution* | Range* | Unit |
|---|---|---|---|---|---|---|---|---|
| Geometrical | Orientation | Discrete | Uniform | [0,45,90,135,180, 225, 270, 315] | – | – | – | ° |
| | Compactness Ratio[1] | Discrete | Categorical | 0.0–0.5 | 0.029 | Uniform | [0.0, 0.5) | – |
| | | | | 0.5–1.0 | 0.273 | | [0.5, 1.0) | |
| | | | | 1.0–1.5 | 0.270 | | [1.0, 1.5) | |
| | | | | 1.5–2.0 | 0.322 | | [1.5, 2.0) | |
| | | | | 2.0–2.5 | 0.089 | | [2.0, 2.5) | |
| | | | | 2.5–3.0 | 0.011 | | [2.5, 3.0) | |
| | | | | 3.0–3.5 | 0.005 | | [3.0, 3.5) | |
| | | | | 3.5–4.0 | 0.000 | | [3.5, 4.0) | |
| | Position of Apartment | Discrete | Uniform | [1–6] | – | – | – | – |
| | Window–wall Ratio[2] | Discrete | Fixed | 32 | – | – | – | % |
| Fabric | Ground Insulation[2], R | Continuous | Triangle | [0.15, 3.50, 0.56] | Triangle PDF[3] | – | – | $m^2$·K/W |

(continued on next page)

**Table D7** (*continued*)

| Category | Parameter | Type | Distribution | Range | Probabilities | Distribution* | Range* | Unit |
|---|---|---|---|---|---|---|---|---|
| | External Wall Insulation[2], R | Continuous | Triangle | [0.19, 3.50, 0.58] | Triangle PDF[3] | – | – | $m^2$·K/W |
| | Roof Insulation[2], R | Continuous | Triangle | [0.22, 3.78, 1] | Triangle PDF[3] | – | – | $m^2$·K/W |
| | Window Insulaiton[2], U | Continous | Triangle | [1.63, 6.2, 3.11] | Triangle PDF[3] | – | – | W/$m^2$·K |
| | External Door Insulation[2], U | Continuous | Triangle | [2.29, 3.4, 3.32] | Triangle PDF[3] | – | – | W/$m^2$·K |
| | Infilteration[3] | Discrete | – | 1: Intermediate-Intermediate | Based on the sampled position of the apartment | Triangle PDF[3,4] | [0.35, 1.5, 1.5] | $dm^3$/s.$m^2$ |
| | | | | 2: Corner-Intermediate | | | [0.455, 1.95, 1.95] | |
| | | | | 3: Intermediate – Ground | | | [0.35, 1.5, 1.5] | |
| | | | | 4: Intermediate-Roof | | | [0.42, 1.8, 1.8] | |
| | | | | 5: Corner-Ground | | | [0.455, 1.95, 1.95] | |
| | | | | 6: Corner – Roof | | | [0.49, 2.1, 2.1] | |
| HVAC | Ventilation system[2] | Discrete | Categorical | [A, C, D] | [0.758, 0.227, 0.015] | – | – | – |
| Occupant and Control | Heating setpoint | Discrete | Uniform | [18–21] | – | – | – | °C |

* Sub-level data: After selecting a bin for the compactness ratio based on its probabilities, a value is sampled uniformly from the range of the chosen bin. For infiltration, the position of the apartment is selected first, followed by the corresponding infiltration range from which a value is then sampled.
[1]Sourced from [45], [2] Sourced from [44], [3] Triangle distribution with [lower limit, upper limit, mode], [4] Calculated using equation (1) [56] in section 3.2.1.2.

**Table D8**
PDFs and Ranges for the interest parameters for the construction year category "1945-1975″ apartment type.

| Category | Parameter | Type | Distribution | Range | Probabilities | Distribution* | Range* | Unit |
|---|---|---|---|---|---|---|---|---|
| Geometrical | Orientation | Discrete | Uniform | [0,45,90,135,180, 225, 270, 315] | – | – | – | ° |
| | Compactness Ratio[1] | Discrete | Categorical | 0.0–0.5 | 0.068 | Uniform | [0.0, 0.5) | – |
| | | | | 0.5–1.0 | 0.367 | | [0.5, 1.0) | |
| | | | | 1.0–1.5 | 0.214 | | [1.0, 1.5) | |
| | | | | 1.5–2.0 | 0.274 | | [1.5, 2.0) | |
| | | | | 2.0–2.5 | 0.063 | | [2.0, 2.5) | |
| | | | | 2.5–3.0 | 0.008 | | [2.5, 3.0) | |
| | | | | 3.0–3.5 | 0.007 | | [3.0, 3.5) | |
| | | | | 3.5–4.0 | 0.000 | | [3.5, 4.0) | |
| | Position of Apartment | Discrete | Uniform | [1–6] | – | – | – | – |
| | Window–wall Ratio[2] | Discrete | Fixed | 40 | – | – | – | % |
| Fabric | Ground Insulation[2], R | Continuous | Triangle | [0.15, 4.15, 0.48] | Triangle PDF[3] | – | – | $m^2$·K/W |
| | External Wall Insulation[2], R | Continuous | Triangle | [0.19,4.18, 0.67] | Triangle PDF[3] | – | – | $m^2$·K/W |
| | Roof Insulation[2], R | Continuous | Triangle | [0.22, 2, 0.96] | Triangle PDF[3] | – | – | $m^2$·K/W |
| | Window Insulaiton[2], U | Continous | Triangle | [1.4, 5.96, 2.87] | Triangle PDF[3] | – | – | W/$m^2$·K |
| | External Door Insulation[2], U | Continuous | Triangle | [2, 3.4, 3.3] | Triangle PDF[3] | – | – | W/$m^2$·K |
| | Infilteration[3] | Discrete | – | 1: Intermediate-Intermediate | Based on the sampled position of the apartment | Triangle PDF[3,4] | [0.35, 1.5, 1.5] | $dm^3$/s.$m^2$ |
| | | | | 2: Corner-Intermediate | | | [0.455, 1.95, 1.95] | |
| | | | | 3: Intermediate – Ground | | | [0.35, 1.5, 1.5] | |
| | | | | 4: Intermediate-Roof | | | [0.42, 1.8, 1.8] | |
| | | | | 5: Corner-Ground | | | [0.455, 1.95, 1.95] | |
| | | | | 6: Corner – Roof | | | [0.42, 2.1, 2.1] | |
| HVAC | Ventilation system[2] | Discrete | Categorical | [A, C, D] | [0.528, 0.460, 0.012] | – | – | – |
| Occupant and Control | Heating setpoint | Discrete | Uniform | [18–21] | – | – | – | °C |

* Sub-level data: After selecting a bin for the compactness ratio based on its probabilities, a value is sampled uniformly from the range of the chosen bin. For infiltration, the position of the apartment is selected first, followed by the corresponding infiltration range from which a value is then sampled.
[1]Sourced from [45], [2] Sourced from [44], [3] Triangle distribution with [lower limit, upper limit, mode], [4] Calculated using equation (1) [56] in section 3.2.1.2.

**Table D9**
PDFs and Ranges for the interest parameters for the construction year category "1975−1995" apartment type.

| Category | Parameter | Type | Distribution | Range | Probabilities | Distribution* | Range* | Unit |
|---|---|---|---|---|---|---|---|---|
| Geometrical | Orientation | Discrete | Uniform | [0,45,90,135,180, 225, 270, 315] | – | – | – | ° |
| | Compactness Ratio[1] | Discrete | Categorical | 0.0–0.5 | 0.088 | Uniform | [0.0, 0.5) | – |
| | | | | 0.5–1.0 | 0.246 | | [0.5, 1.0) | |
| | | | | 1.0–1.5 | 0.311 | | [1.0, 1.5) | |
| | | | | 1.5–2.0 | 0.253 | | [1.5, 2.0) | |
| | | | | 2.0–2.5 | 0.085 | | [2.0, 2.5) | |
| | | | | 2.5–3.0 | 0.015 | | [2.5, 3.0) | |
| | | | | 3.0–3.5 | 0.004 | | [3.0, 3.5) | |
| | | | | 3.5–4.0 | 0.000 | | [3.5, 4.0) | |
| | Position of Apartment | Discrete | Uniform | [1–6] | – | – | – | – |
| | Window–wall Ratio[2] | Discrete | Fixed | 33 | – | – | – | % |
| Fabric | Ground Insulation[2], R | Continuous | Triangle | [0.52, 3.50, 1.16] | Triangle PDF[3] | – | – | $m^2 \cdot K/W$ |
| | External Wall Insulation[2], R | Continuous | Triangle | [0.8, 3.5, 1.66] | Triangle PDF[3] | – | – | $m^2 \cdot K/W$ |
| | Roof Insulation[2], R | Continuous | Triangle | [1.3, 3.78, 1.66] | Triangle PDF[3] | – | – | $m^2 \cdot K/W$ |
| | Window Insulaiton[2], U | Continous | Triangle | [1.73, 5.4, 2.91] | Triangle PDF[3] | – | – | $W/m^2 \cdot K$ |
| | External Door Insulation[2], U | Continuous | Triangle | [2, 3.4, 3.32] | Triangle PDF[3] | – | – | $W/m^2 \cdot K$ |
| | Infilteration[3] | Discrete | – | 1: Intermediate-Intermediate | Based on the sampled position of the apartment | Triangle PDF[3,4] | [0.35, 1.25, 1] | $dm^3/s.m^2$ |
| | | | | 2: Corner-Intermediate | | | [0.455, 1.63, 1.30] | |
| | | | | 3: Intermediate – Ground | | | [0.35, 1.25, 1] | |
| | | | | 4: Intermediate-Roof | | | [0.42, 1.5, 1.2] | |
| | | | | 5: Corner-Ground | | | [0.455, 1.625, 1.30] | |
| | | | | 6: Corner – Roof | | | [0.49, 1.75, 1.4] | |
| HVAC | Ventilation system[2] | Discrete | Categorical | [A, C, D] | [0.206, 0.781, 0.013] | – | – | – |
| Occupant and Control | Heating setpoint | Discrete | Uniform | [18–21] | – | – | – | °C |

* Sub-level data: After selecting a bin for the compactness ratio based on its probabilities, a value is sampled uniformly from the range of the chosen bin. For infiltration, the position of the apartment is selected first, followed by the corresponding infiltration range from which a value is then sampled.
[1]Sourced from [45], [2] Sourced from [44], [3] Triangle distribution with [lower limit, upper limit, mode], [4] Calculated using equation (1) [56] in section 3.2.1.2.

**Table D10**
PDFs and Ranges for the interest parameters for the construction year category "after 1995" apartment type.

| Category | Parameter | Type | Distribution | Range | Probabilities | Distribution* | Range* | Unit |
|---|---|---|---|---|---|---|---|---|
| Geometrical | Orientation | Discrete | Uniform | [0,45,90,135,180, 225, 270, 315] | – | – | – | ° |
| | Compactness Ratio[1] | Discrete | Categorical | 0.0–0.5 | 0.154 | Uniform | [0.0, 0.5) | – |
| | | | | 0.5–1.0 | 0.355 | | [0.5, 1.0) | |
| | | | | 1.0–1.5 | 0.175 | | [1.0, 1.5) | |
| | | | | 1.5–2.0 | 0.231 | | [1.5, 2.0) | |
| | | | | 2.0–2.5 | 0.043 | | [2.0, 2.5) | |
| | | | | 2.5–3.0 | 0.041 | | [2.5, 3.0) | |
| | | | | 3.0–3.5 | 0.000 | | [3.0, 3.5) | |
| | | | | 3.5–4.0 | 0.000 | | [3.5, 4.0) | |
| | Position of Apartment | Discrete | Uniform | [1–6] | – | – | – | – |
| | Window–wall Ratio[2] | Discrete | Fixed | 38 | – | – | – | % |
| Fabric | Ground Insulation[2], R | Continuous | Triangle | [0.82, 4.59, 2] | Triangle PDF[3] | – | – | $m^2 \cdot K/W$ |
| | External Wall Insulation[2], R | Continuous | Triangle | [1.69, 5.69, 2.61] | Triangle PDF[3] | – | – | $m^2 \cdot K/W$ |
| | Roof Insulation[2], R | Continuous | Triangle | [2.5, 3.5, 2.67] | Triangle PDF[3] | – | – | $m^2 \cdot K/W$ |
| | Window Insulaiton[2], U | Continous | Triangle | [1., 4.1, 2.16] | Triangle PDF[3] | – | – | $W/m^2 \cdot K$ |
| | External Door Insulation[2], U | Continuous | Triangle | [2, 3.4, 3.28] | Triangle PDF[3] | – | – | $W/m^2 \cdot K$ |
| | Infilteration[3] | Discrete | – | 1: Intermediate-Intermediate | Based on the sampled position of the apartment | Triangle PDF[3,4] | [0.35, 0.75, 0.50] | $dm^3/s.m^2$ |
| | | | | 2: Corner-Intermediate | | | [0.455, 0.98, 0.65] | |
| | | | | 3: Intermediate – Ground | | | [0.35, 0.75, 0.50] | |
| | | | | 4: Intermediate-Roof | | | [0.42, 0.9, 0.6] | |
| | | | | 5: Corner-Ground | | | [0.455, 0.975, 0.65] | |
| | | | | 6: Corner – Roof | | | [0.49, 1.05, 0.7] | |
| HVAC | Ventilation system[2] | Discrete | Categorical | [A, C, D] | [0.014, 0.781, 0.196] | – | – | – |
| Occupant and Control | Heating setpoint | Discrete | Uniform | [18–21] | – | – | – | °C |

* Sub-level data: After selecting a bin for the compactness ratio based on its probabilities, a value is sampled uniformly from the range of the chosen bin. For infiltration, the position of the apartment is selected first, followed by the corresponding infiltration range from which a value is then sampled.
[1]Sourced from [45], [2] Sourced from [44], [3] Triangle distribution with [lower limit, upper limit, mode], [4] Calculated using equation (1) [56] in section 3.2.1.2.

## Appendix E:. Appropriate sampling size in LT (55/35 °C) supply

Figures E.1 and E.2 illustrate the parameter ranking, absolute SRRC, and $R^2$ values for the two output parameters for terraced-intermediate and apartment dwellings, respectively, under an LT supply of 55/35 °C. From both graphs, it can be observed that convergence reached around 1300 samples, with the $R^2$ value being the highest.

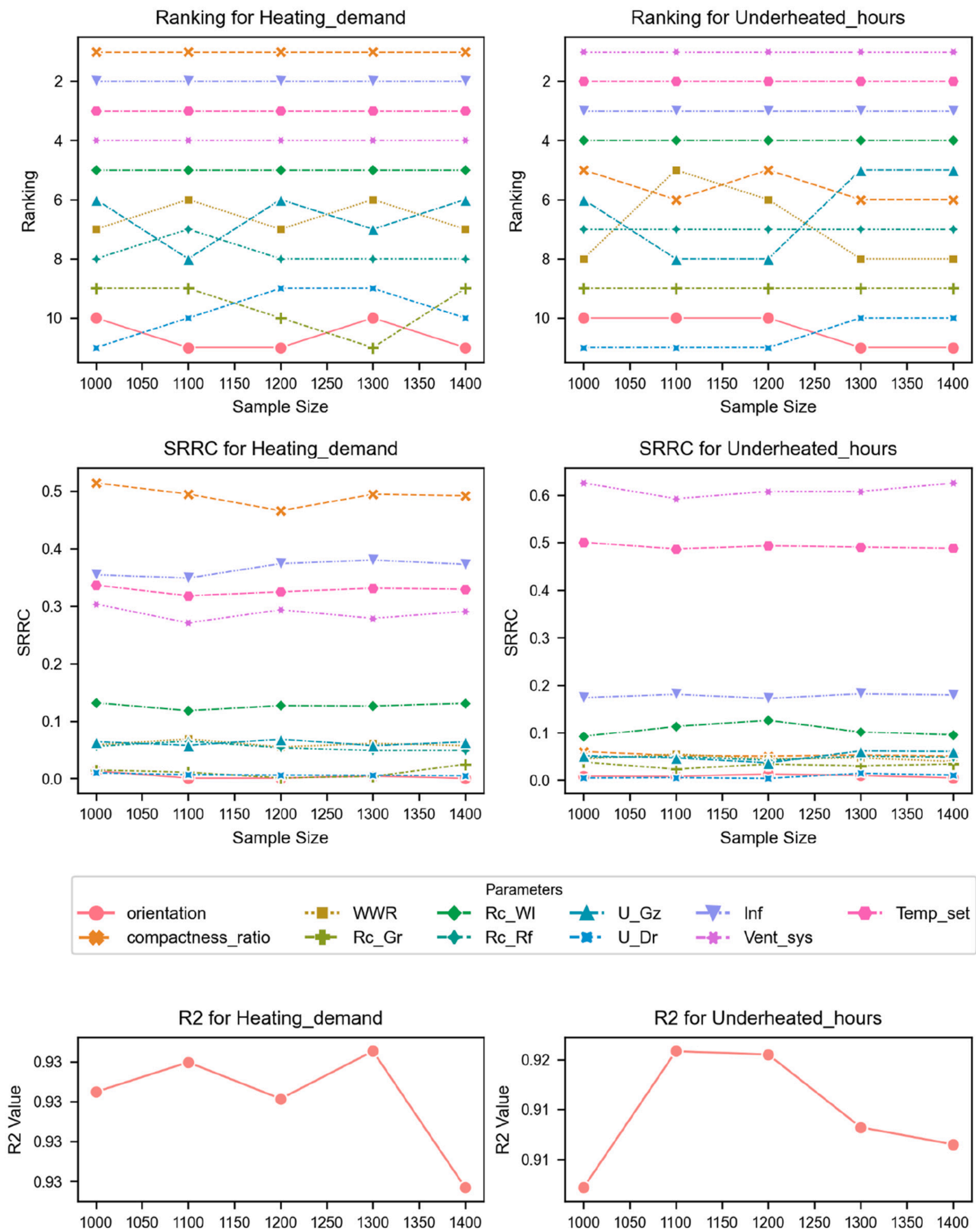


**Fig. E1.** Parameter ranking, SRRC absolute and R2 values of terraced-intermediate dwelling type for the two output parameters under LT supply of 55/35 °C.

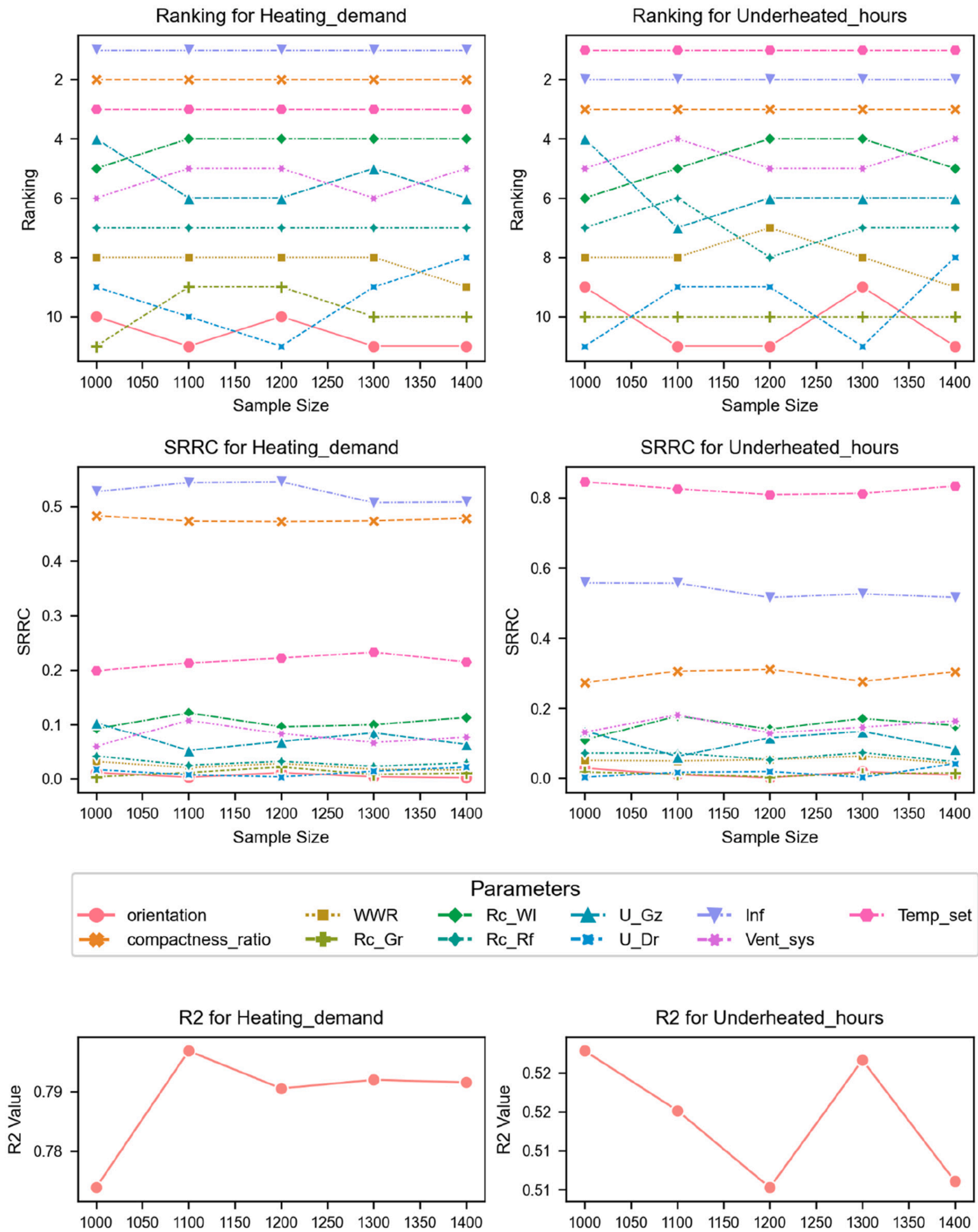


**Fig. E2.** Parameter ranking, SRRC absolute and R2 values of apartment dwelling type for the two output parameters under LT supply of 55/35 °C.

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