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The Impact of Building Level of Detail Modelling Strategies: Insights into Building and Urban Energy Modelling

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Abstract: Level of detail (LoD) is an important factor in urban building energy modelling (UBEM), affecting functionality and accuracy. This work assesses the impacts of the LoD of the roof, window, and zoning on a comprehensive range of outcomes (annual heating load, peak heating demand, overheating, and time-series heating error) in a representative New Zealand house. Lower-LoD roof scenarios produce mean absolute error results ranging from 1.5% for peak heating power to 99% for overheating. Windows and shading both affect solar gains, so lower-LoD windows and/or shading elements can considerably reduce model accuracy. The LoD of internal zoning has the greatest effect on time-series accuracy, producing mean absolute heating error of up to 66 W. These results indicate that low-LoD "shoebox" models, common in UBEM, can produce significant errors which aggregate at scale. Accurate internal zoning models and accurate window size and placement have the greatest potential for error reduction, but their implementation is limited at scale due to data availability and automation barriers. Conversely, modest error reductions can be obtained via simple model improvements, such as the inclusion of eaves and window border shading. Overall, modellers should select LoD elements according to specific accuracy requirements.

Keywords: urban building energy modelling; level of detail; model accuracy; sensitivity analysis

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1. Introduction

Physics-based urban building energy modelling (UBEM) represents buildings at the urban scale, from dozens to thousands of buildings, by modelling energy and mass flows in and around buildings and capturing the interactions between buildings, which are not present when modelling buildings individually [1]. With its ability to capture urban energy use patterns accurately, UBEM is commonly used to inform urban planning, energy network design, and sustainable development, to forecast the effects of energy efficiency interventions, and to construct digital twin models [2].

Different UBEM applications focus on different outputs. For example, energy scenario and strategy planning often focuses on aggregate energy consumption [3] and the capital and operational costs of different strategies [4]; energy network and systems design requires the accurate assessment of aggregate peak energy loads at different network nodes [5]; and digital twin modelling requires reliable short-term forecasts of energy supply and demand for the control and coordination of distributed energy resources (DER) and demand responses [6].

Depending on desired modelling outcomes and available data, buildings are modelled with varying levels of detail (LoDs). The LoD denotes the geometric fidelity with which building elements, such as external dimensions, windows, and internal zoning, are represented [7]. For example, multiple windows could be modelled with placement and dimensions matching the real building or with a single window of equivalent total area [8].

One example of varying LoDs is the gbXML format, a common BEM file format which categorises whole-building models with a five-level LoD schema [9]. However, the gbXML schema is non-exhaustive as building elements themselves can have variable levels of detail. In general, higher LoD indicates higher physical fidelity and complexity and thus greater computational requirements and increased modelling effort necessary to produce models. Conversely, lower-LoD models can reduce modelling effort and computational requirements; however, the lower physical fidelity may reduce model accuracy [10]. For example, a single equivalent-area window is much simpler to implement than multiple windows; however, due to differing window distribution, the single window will not accurately capture the impact of shading and solar heating.

UBEMs typically utilise simple "shoebox" models with low LoD [11,12], which represent each building as a simple extrusion of the building footprint to the building height, with a single thermal zone per floor and assumed window-to-wall area ratios. While these shoebox models can be less accurate than higher-LoD models, they are widely used for urban-scale UBEMs due to their low complexity and simple automated creation and the wide availability of relevant data, building footprints, and predeveloped construction archetypes [13].

While model LoD can greatly impact the accuracy of results, the extent of this impact on models with differing LoDs has not yet been thoroughly assessed. Thus, the trade-offs between LoD strategies and the accuracy of various assessments is unknown. In particular, the overall accuracy of widely used UBEMs with simplified LoDs, such as shoebox models, are unquantified.

1.1. Literature Review

Previous work has assessed the impacts of input variables on a range of measures of UBEM model accuracy. Sensitivity analyses have been conducted to determine the effects of building construction [14–17], occupant behaviour [18,19], and other key input parameters, such as air flow, on total energy demand and aggregate heating/cooling demand [20]. However, these analyses focus only on aggregate outcomes (total energy demand and aggregate heating/cooling demand) and do not consider time-sensitive variables such as peak demands or time-series error, which are required for understanding applications in which real-time demand is an important factor.

Peak energy demand has also been assessed, with sensitivity analyses investigating the impacts of building construction and use parameters [21,22] and the uncertainties of operational, geometrical, and physical building parameters [23]. These peak demand analyses complement the aggregate outcomes assessed in other work. However, the time-sensitive components of these analyses are limited to a single point (i.e., the time of the peak event), which still does not fully inform real-time outcomes.

The impact of LoD in BEM has also been studied. In a case study of an educational building in the Netherlands, the higher LoD of windows, shading, and building interior geometry was shown to produce more-accurate assessments of total energy consumption [24]. For a district-level case study in Sweden, the LoD of building geometry, thermal zoning, and external shading were all shown to have a significant impact on building-level energy demand, and lower-detail shading models were shown to produce up to 10% error in aggregate district-level energy demand [25]. However, these analyses assessed only total energy consumption at both building and district levels and did not investigate time-series accuracy or other assessments of overall model accuracy.

Overall, research has focused on aggregate outcomes, such as total energy demand and aggregate heating/cooling demand, and individual peak demand events. Other outcomes of interest, such as overall time-series accuracy, have been largely overlooked, and no research to date has assessed the impacts of different LoD modelling strategies on overall model accuracy. These other outcomes are increasingly important, as accurate time-series predictions are required for digital twin models and the successful integration of energy demand response. Furthermore, the increasing adoption of low-LoD models, such as shoebox models, necessitates the understanding of the effects of model LoD on overall model accuracy, which is not fully reflected by aggregate outcomes and individual peak events and thus requires a comprehensive range of assessments.

1.2. Contributions

This work assesses the impacts on overall model accuracy of varying LoD strategies for building elements, including roof, windows, and internal zoning. Several assessments are employed to evaluate overall accuracy according to a comprehensive range of energy applications for UBEM: peak and total heating energy demand, overheating, and time-series heating error. These strategies are implemented in a three-bedroom stand-alone house, representative of the residential building stock in Christchurch, New Zealand, for a range of common construction and heating usage scenarios. Results are generated for New Zealand, but the relative impact of LoD strategies is widely generalisable to other countries and regions.

With its quantification of the effects of model LoD on a range of accuracy measures, using time-series assessments alongside aggregate and peak demand assessments, this work addresses the research gaps identified in Section 1.1 and contributes to the overall understanding of the accuracy of UBEMs for its various applications. The results of this work have important implications for urban planning, energy forecasting, and energy efficiency and GHG emissions reduction strategies and can inform the appropriate selection of model LoD strategy according to required accuracy, modelling effort limitations, and data availability.

1.3. Structure

This work is laid out as follows: Section 2 describes the building model, scenarios, and assessments; Section 3 presents the results of the analyses; and Sections 4 and 5 provide discussion and conclusions, respectively.

2. Materials and Methods

2.1. Materials

To generate results useful to the New Zealand residential building stock, a single-story, three-bedroom, 130 m^2 stand-alone house is chosen, which is the most representative single building for New Zealand [26]. A real building of this type is modelled from building plans to reduce idealising assumptions. The selected building is on concrete slab foundation, walls are timber framing with brick veneer, and windows are thermally broken aluminium framed with double-glazing. The dwelling was built in 2014, and its building plans are shown in Figure 1.

The selected weather file is a typical meteorological year (TMY) file for Christchurch, New Zealand [27]. New Zealand is a temperate climate, subject to both heating and cooling requirements [28], so the results generated from this work can provide general insights for a wide variety of other climates as the impacts of both environmental heating and cooling are present.

2.2. Methodology

Modelling geometries for the representative building are generated for several LoD strategies, described in Section 2.2.1, including roof, window, and zoning representations of increasing fidelity. A representation of the full-LoD building model is shown in Figure 2. Building model generation and simulation is executed in the commercial building energy modelling software DesignBuilder [29], a front end for the EnergyPlus simulation engine [30].

For each LoD strategy, a full range of relevant construction and usage profiles are modelled, presenting 63 scenarios for assessment. The construction and usage profiles present a comprehensive range of insulation levels and practical heating behaviours, representing the variability present for the residential building stock in New Zealand. Thus, the results are not constrained by assumed insulation levels or heating behaviours. The usage and construction profiles are detailed in Section 2.2.2.

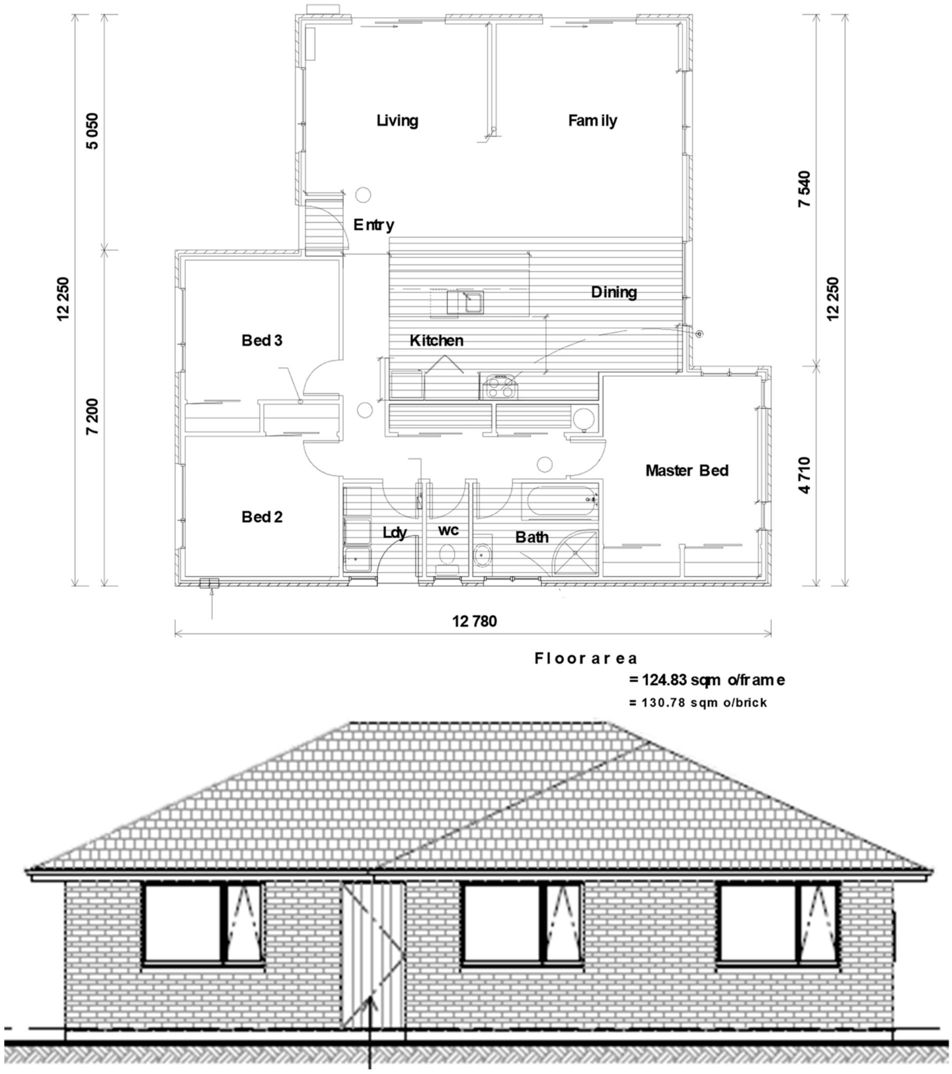

Figure 1. Building plan and elevation of the modelled house.

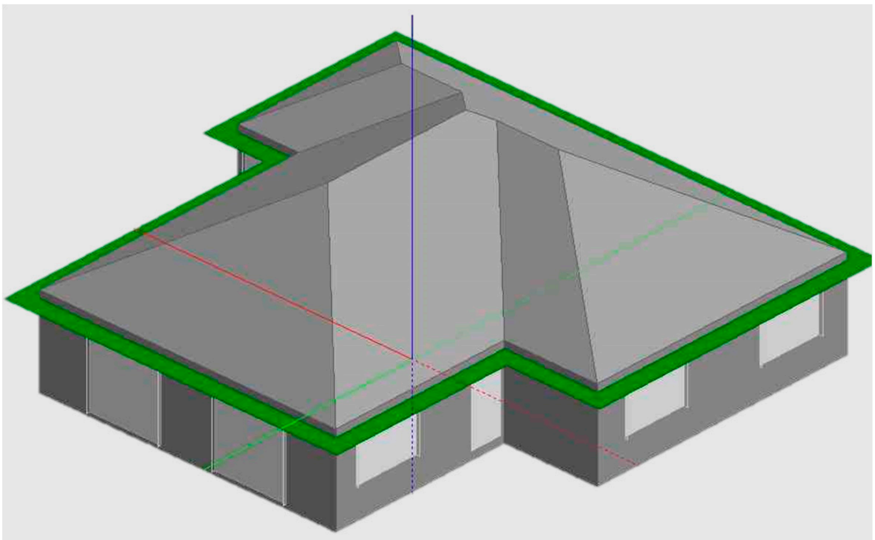

Figure 2. Representative BEM, modelled with full LoD in DesignBuilder (Version 7.0.2.006).

Full annual building energy and comfort simulations are conducted for each scenario, which are combinations of LoD strategy and construction and usage profiles. A full list of scenarios is included in Section 2.2.3. Simulations are conducted with a time resolution of 15 min. Several assessments are evaluated from the results: annual heating load, peak heating power, overheating, and time-series error in heating power. Assessment definitions and calculation methods are detailed in Section 2.2.4.

Simulation settings and building characteristics, where not detailed in the proceeding sections, are included in the Appendix A.

A flowchart of the methodology is shown in Figure 3, which contextualises the inputs, baseline model, analysed scenarios, and assessments.

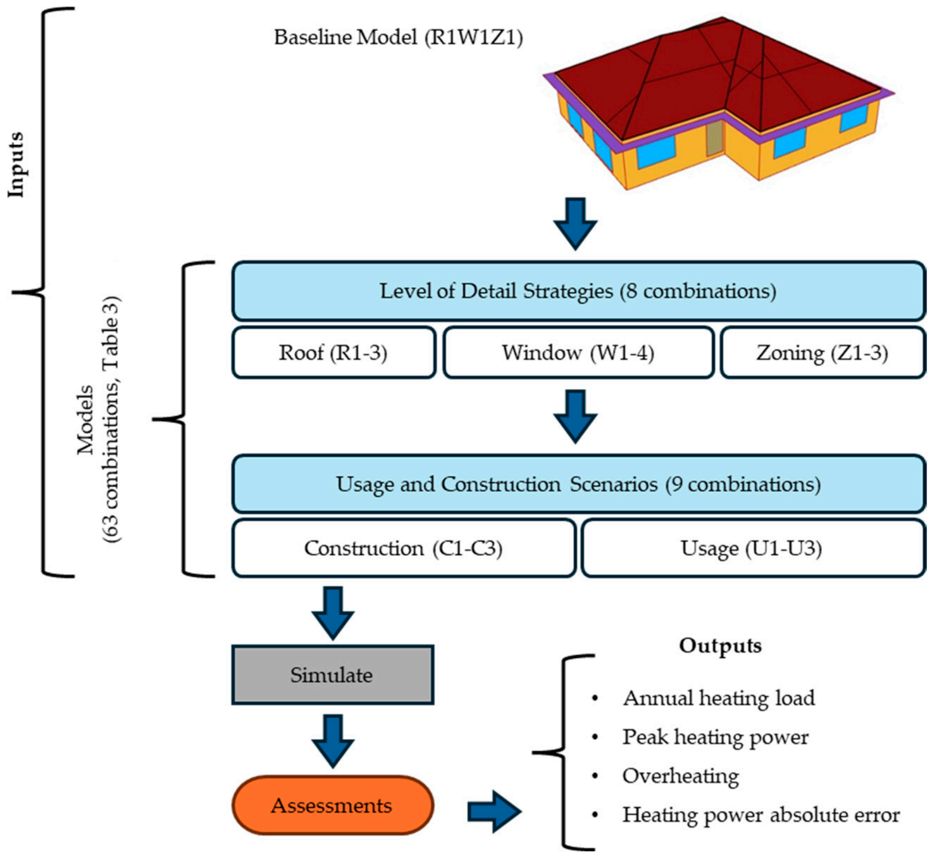

Figure 3. Flowchart showing the modelling methodology, including inputs and assessments.

2.2.1. Level of Detail Strategies

The geometric representations of building elements are modelled in various fidelities (LoD). The building elements considered are the roof, window, and internal zoning, of which three, four, and three strategies are derived, respectively. Representation options are listed below.

Roof LoD

Roof representations include roof air volumes and eaves shading, as shown in Figure 4. Strategy R1 includes a pitched roof with internal air volume. The geometries closely approximate the roof as built. Shading devices are included at 2.2 m height and 0.8 m width and vertical positioning to replicate the impact of shading from eaves. Strategy R2 includes a flat roof with shading devices to replicate eaves shading. Strategy R3 includes a flat roof with no shading devices.

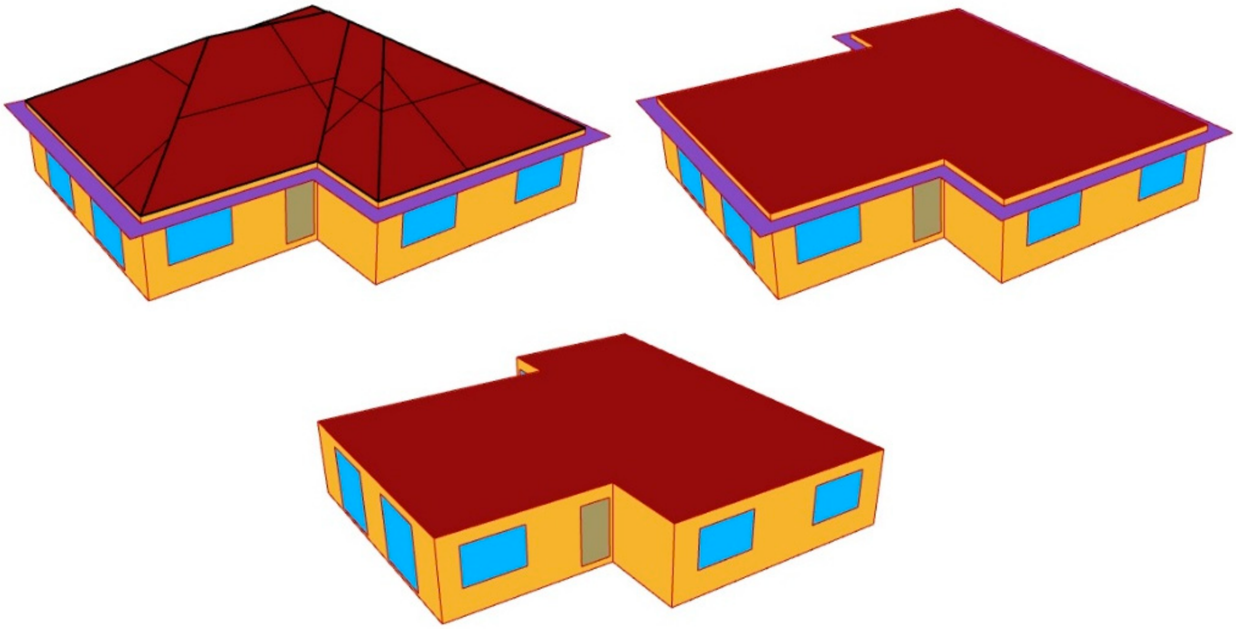

Figure 4. Roof models: R1 (**top left**); R2 (**top right**); and R3 (**bottom**).

Window LoD

Window representations include various arrangements of window distribution and placement and window border shading to represent window recession, as shown in Figure 5. Strategy W1 matches the placement and size of the real windows and includes border shading. Strategy W2 matches the placement and size of the real windows and does not include border shading. Strategy W3 provides a single window per wall with equivalent area to the sum of the real windows on that face. Windows are centred in the wall and border shades are not included. Strategy W4 provides a single window per wall centred to the wall centre, with an area fixed by the window-to-wall area ratio of the building, which is 22% for this building. Thus, strategy W4 distributes total building window area evenly over all the building's walls.

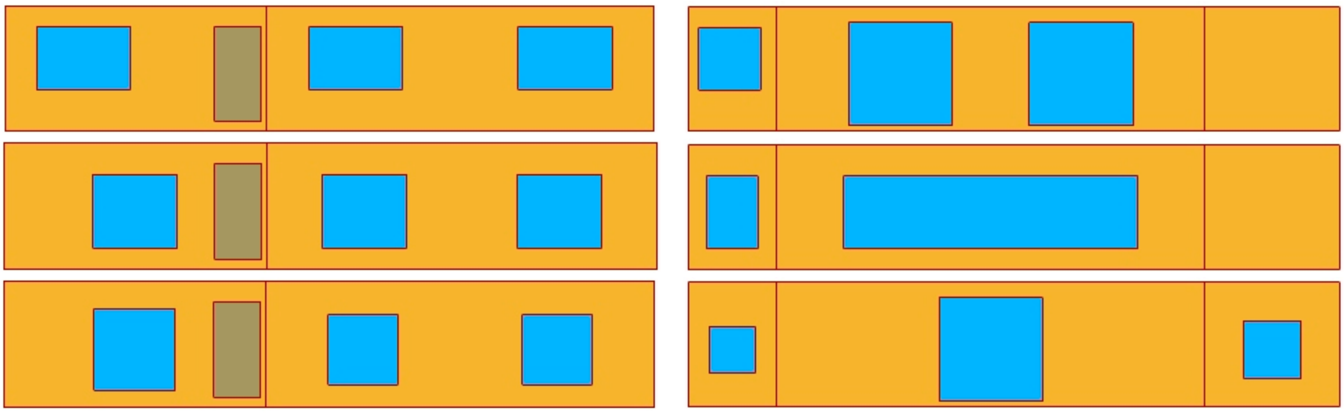

Figure 5. The left and back views of the modelled house for different window models. Window models W1 and 2 (**top**) reflect the windows as built; W3 (**middle**) uses one equivalent area window to replace individual windows per face; and W4 (**bottom**) uses one single centred window per face with the area set by a window-to-wall area ratio.

Zoning LoD

Three zoning strategies are presented, representing internal layout, as shown in Figure 6. As the modelled house is an open-plan layout, the kitchen, living, and dining rooms are combined. Strategy Z1 is fully zoned, with thermal zones representing each room in the building, including a combined kitchen-living-dining room (henceforth referred to as the "living area"), three bedrooms, laundry, bathroom, and toilet. Strategy Z2 divides zones based on frequency of occupancy and has only two thermal zones, including a zone for the living area and bedrooms, and a zone for the laundry, bathroom, and toilet. Strategy Z3 presents a single thermal zone containing all the rooms, which is the most common modelling scenario in UBEM applications [11,12].

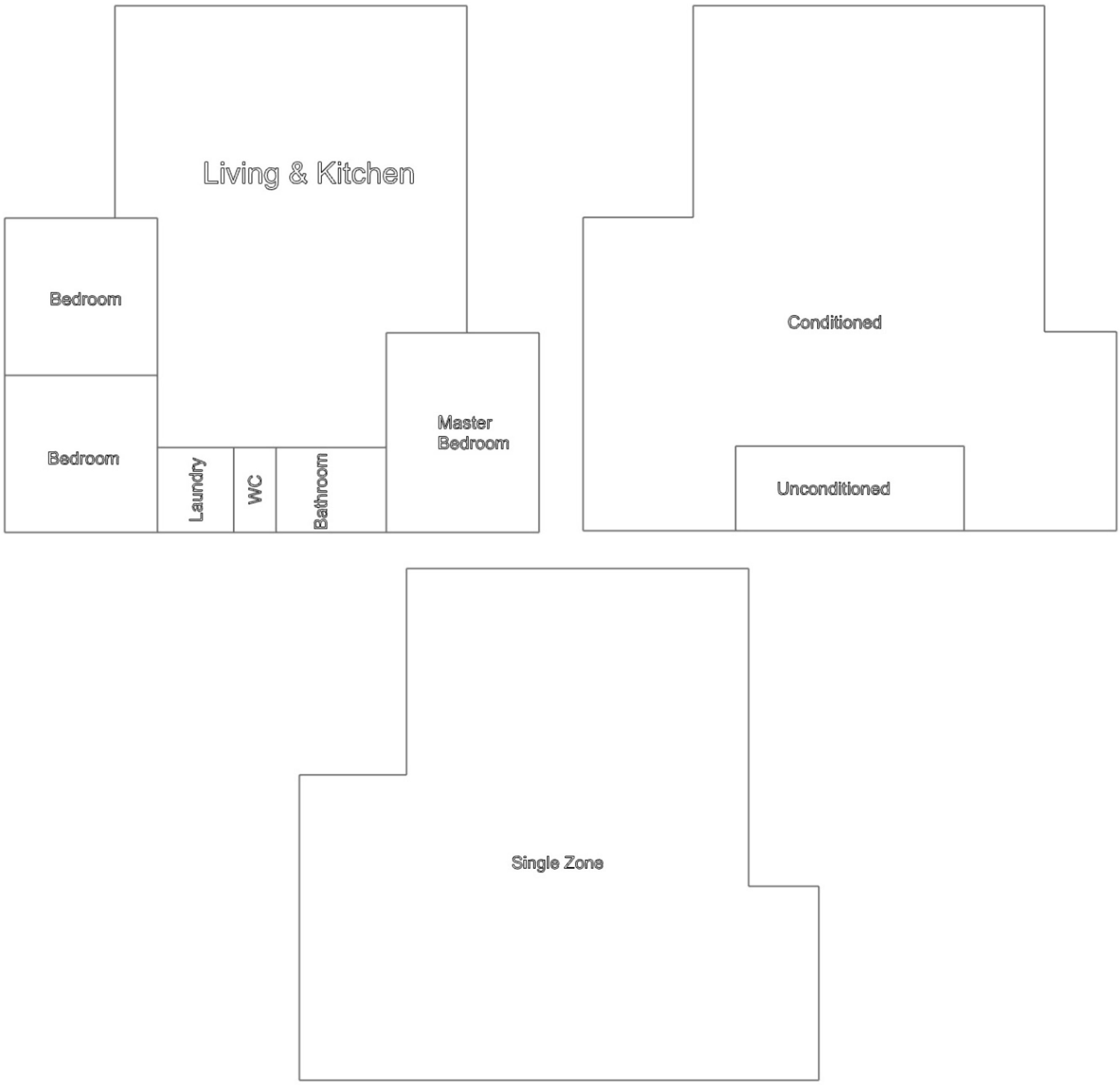

Figure 6. Zoning models: Z1 (**top left**); Z2 (**top right**); Z3 (**bottom**).

2.2.2. Construction and Usage Profiles

Three construction and usage profiles are utilised in scenario analysis to capture a range of practical insulation levels and heating behaviours and thus assess the relative sensitivity of LoD strategies under a range of practical conditions.

Construction Profiles

Three construction profiles are utilised in scenario analysis, denoted as C1–3 and representing varying levels of building insulation in the ceiling and external walls in line with the state of insulation in the New Zealand building stock. Profile C1 includes fully insulated external walls and ceiling with total insulation values of R 1.67 W/m^{2}K and R 3.90 W/m^{2}K, respectively. Profile C2 includes a fully insulated ceiling (R 3.90 W/m^{2}K) and non-insulated walls (R 0.58 W/m^{2}K). Profile C3 includes non-insulated external walls and ceiling with total insulation values of R 0.58 m^{2}K/W and R 0.72 m^{2}K/W, respectively. The construction scenarios are summarised in Table 1, and baseline constructions for the building and additional construction profiles are included in Appendix A in Tables A3–A5.

Table 1. R-Values for external surfaces for each construction profile.

	Ext Walls (m^{2}K/W)	Ceiling (m^{2}K/W)	Floor (m^{2}K/W)	Windows (m^{2}K/W)
C1	1.67	3.90	1.60	0.37
C2	0.58	3.90	1.60	0.37
C3	0.58	0.72	1.60	0.37

Usage Profiles

Three "usage" profiles are utilised, denoted as U1–3 and summarised in Table 2. Profile U1 provides continuous heating of the entire floor plan, a scenario common in UBEM analysis. Profile U2 provides continuous heating to frequently occupied areas (i.e., the living area and bedrooms). Profile U3 provides intermittent heating in the living area between 6 a.m. and 10 p.m. and the bedrooms between 8 p.m. and 7 a.m. In all cases, the temperature setpoint is 20 °C.

Table 2. Heating areas and schedules for usage profiles.

	Areas	Schedule	Setpoint
U1	Whole floor plan	Always on	20 °C
U2	Living area and bedrooms	Always on	20 °C
U3	Living area	6 a.m.–10 p.m.	20 °C
	Bedrooms	8 p.m.–7 a.m.	20 °C

2.2.3. Modelling Scenarios

Modelling scenarios consist of combinations of LoD strategies with relevant construction and usage profiles applied. Altogether, 63 scenarios are modelled, which are listed in Table 3. Practical limitations restrict the application of usage profiles U2 and U3 in the case of LoD strategies Z2 and Z3 as multiple zones are required.

Table 3. Table containing combinations of LoD strategies and construction and usage profiles that were tested. The first row, underlined, also indicates the reference scenarios.

LoD \ C and U	C1U1	C2U1	C3U1	C1U2	C2U2	C3U2	C1U3	C2U3	C3U3
R1W1Z1	R1W1Z1 -C1U1	R1W1Z1 -C2U1	R1W1Z1 -C3U1	R1W1Z1 -C1U2	R1W1Z1 -C2U2	R1W1Z1 -C3U2	R1W1Z1 -C1U3	R1W1Z1 -C2U3	R1W1Z1 -C3U3
R2W1Z1	R2W1Z1 -C1U1	R2W1Z1 -C2U1	R2W1Z1 -C3U1	R2W1Z1 -C1U2	R2W1Z1 -C2U2	R2W1Z1 -C3U2	R2W1Z1 -C1U3	R2W1Z1 -C2U3	R2W1Z1 -C3U3
R3W1Z1	R3W1Z1 -C1U1	R3W1Z1 -C2U1	R3W1Z1 -C3U1	R3W1Z1 -C1U2	R3W1Z1 -C2U2	R3W1Z1 -C3U2	R3W1Z1 -C1U3	R3W1Z1 -C2U3	R3W1Z1 -C3U3

Table 3. *Cont.*

LoD \ C and U	C1U1	C2U1	C3U1	C1U2	C2U2	C3U2	C1U3	C2U3	C3U3
R1W2Z1	R1W2Z1 -C1U1	R1W2Z1 -C2U1	R1W2Z1 -C3U1	R1W2Z1 -C1U2	R1W2Z1 -C2U2	R1W2Z1 -C3U2	R1W2Z1 -C1U3	R1W2Z1 -C2U3	R1W2Z1 -C3U3
R1W3Z1	R1W3Z1 -C1U1	R1W3Z1 -C2U1	R1W3Z1 -C3U1	R1W3Z1 -C1U2	R1W3Z1 -C2U2	R1W3Z1 -C3U2	R1W3Z1 -C1U3	R1W3Z1 -C2U3	R1W3Z1 -C3U3
R1W4Z1	R1W4Z1 -C1U1	R1W4Z1 -C2U1	R1W4Z1 -C3U1	R1W4Z1 -C1U2	R1W4Z1 -C2U2	R1W4Z1 -C3U2	R1W4Z1 -C1U3	R1W4Z1 -C2U3	R1W4Z1 -C3U3
R1W1Z2	R1W1Z2 -C1U1	R1W1Z2 -C2U1	R1W1Z2 -C3U1	R1W1Z2 -C1U2	R1W1Z2 -C2U2	R1W1Z2 -C3U2	-	-	-
R1W1Z3	R1W1Z3 -C1U1	R1W1Z3 -C2U1	R1W1Z3 -C3U1	-	-	-	-	-	-

2.2.4. Assessments

Each scenario in Table 3 is simulated for a full year, and time-series results for operative zone temperature (T_z [°C]) and zone heating load ($P_{heat,zone}$ [W]) are extracted. Four assessments are calculated from the results: annual heating load, peak heating power required, overheating, and absolute error in time series heating power. The assessments are calculated as outlined below. Results are presented relative to the most detailed LoD strategy (R1W1Z1) assessed under the same construction and usage profiles; i.e., the reference scenario for R1W4Z1C3U2 is R1W1Z1C3U2.

Annual heating load ($E_{heat,bldg}$ [Wh]) is simply the cumulative heating load for all zones for a full year, and is defined as follows:

$$P_{heat,bldg} = \sum_{z} P_{heat,zone}, \tag{1}$$

$$E_{heat,bldg} = \sum_{t=1}^{t=n} P_{heat,bldg}.\Delta t, \tag{2}$$

where $P_{heat,bldg}$ is the heating power (W) required for the building, z denotes a thermal zone, t denotes the hour in the year, and n denotes the number of timesteps (Δt) in the series.

Peak heating power ($P_{heat,max}$ [W]) is the maximum power demand in the annual dataset, defined as follows:

$$P_{heat,max} = \max\left(P_{heat,bldg}\right). \tag{3}$$

Overheating [°C·Hrs] is the area-weighted sum of degree-hours where the temperature exceeds 26 °C, defined as follows:

$$\text{Overheating} = \sum_{t=1}^{t=n} \sum_{z} \frac{(T_z - T_{OH}) \cdot A_z}{A_T} \cdot H(T_z - T_{OH}) \cdot \Delta t, \tag{4}$$

where T_z is the temperature for the thermal zone, T_{OH} is the overheating threshold, A_z is the zone floor area, A_T is the total floor area, and H is a Heaviside function, which evaluates as 1 when the temperature exceeds the threshold and 0 when the temperature is under the threshold.

Time-series heating power is evaluated as the mean absolute error relative to the reference scenario, i.e., the highest LoD strategy under the same construction and usage; it is defined as follows:

$$P_{heat,AE} = \frac{1}{n}\sum_{t=1}^{n}\left|P_{heat,bldg,ref,t} - P_{heat,bldg,t}\right|. \quad (5)$$

3. Results

The impacts of LoD strategies across construction and usage profiles are presented in Sections 3.1–3.3. For each LoD element (roof, window, zone), the aggregate results for each assessment across all strategies (i.e., R1, R2, R3, etc.) and the distribution of results across the construction and usage profiles are presented as two distinct figures.

Aggregate results are presented as bar plots, such as in Figure 7, where the magnitude represents the mean absolute error (MAE) across construction and usage profiles, and error bars present the range in real error, representing the minimum and maximum across the construction and usage profiles. The distribution for each LoD across construction and usage are presented, such as in Figure 8, as colour-mapped tables, which visualise the difference between each scenario and the highest LoD.

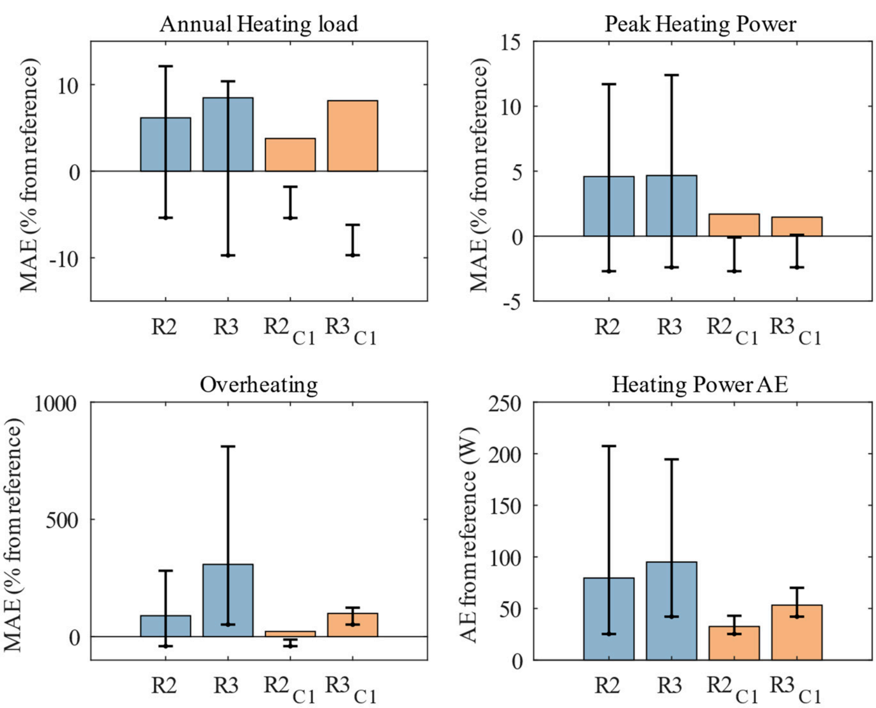

Figure 7. MAE of different roof LoD strategies across construction and usage profiles and minimum and maximum values.

R2

Annual heating load [%]

	U1	U2	U3
C1	-5.4	-1.8	-4.1
C2	-4.5	-4.5	-3
C3	12.1	9.9	10

Peak heating power [%]

	U1	U2	U3
C1	-2.7	-2.3	-0.1
C2	-2.2	-2.4	0.5
C3	9.7	-9.6	11.8

Overheating [%]

	U1	U2	U3
C1	-13	-41	-13
C2	-12	-11	-11
C3	14	281	278

Heating power AE [W]

	U1	U2	U3
C1	43	29	25
C2	52	49	30
C3	207	172	107

R3

Annual heating load [%]

	U1	U2	U3
C1	-9.7	-6.2	-8.5
C2	-8.7	-8.7	-7.3
C3	10.4	8.4	8.3

Peak heating power [%]

	U1	U2	U3
C1	-2.4	-2.1	0.1
C2	-1.6	-1.8	0.9
C3	10.4	10.3	12.4

Overheating [%]

	U1	U2	U3
C1	122	51	123
C2	123	124	126
C3	483	811	809

Heating power AE [W]

	U1	U2	U3
C1	70	48	42
C2	91	85	54
C3	195	168	104

Figure 8. Distribution of error for different roof LoD strategies across construction and usage profiles.

3.1. Roof

The impacts of roof LoD strategy (R2 and R3) on annual heating load, peak heating power, overheating, and heating power are shown in Figure 7. The distribution of results across construction and usage profiles are presented in Figure 8.

As expected, the presence of roof insulation has a considerable impact on the magnitude of error in all assessments, in many cases reversing the trend. For this reason, results $R2_{C1}$ and $R3_{C1}$, i.e., the mean of the fully insulated C1 construction profiles, are also included in Figure 7.

Generally, MAE increases with decreasing LoD. R2 uses a flat roof, the removal of the airspace, and underpredicts annual heating load by 2–5%, overheating by 13–41%, and peak heating power by 0–3% in the insulated case. R3 further removes the eaves shading and underpredicts annual heating load by 6–10%, overpredicts overheating by 51–123%, and underpredicts peak heating power by 0–2% for the insulated case. While peak heating load is relatively unchanged, the average absolute heating power increases by approximately 50% between R3 and R2, demonstrating more significant changes in temporal demand patterns than is suggested by peak load.

3.2. Windows

The impacts of a window LoD strategy (W2, W3, and W4) on annual heating load, peak heating power, overheating, and heating power are shown in Figure 9. The distribution of results across construction and usage profiles are presented in Figure 10.

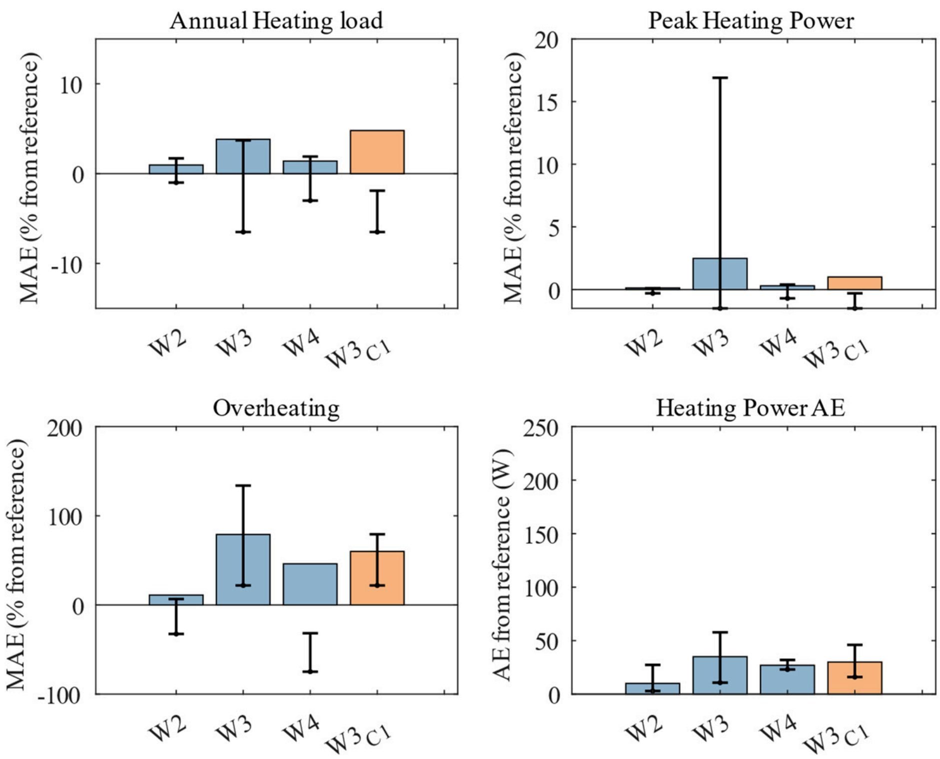

Figure 9. MAE of different window LoD strategies across construction and usage profiles and minimum and maximum values.

Window LoD affects error, as shown in Figures 9 and 10. W2 represents the removal of border shading, W3 additionally replaces the as-built windows with a single centred window of equivalent area on each face, and W4 applies an average window-to-wall area ratio (22%) on each face, uniformly distributing the windows.

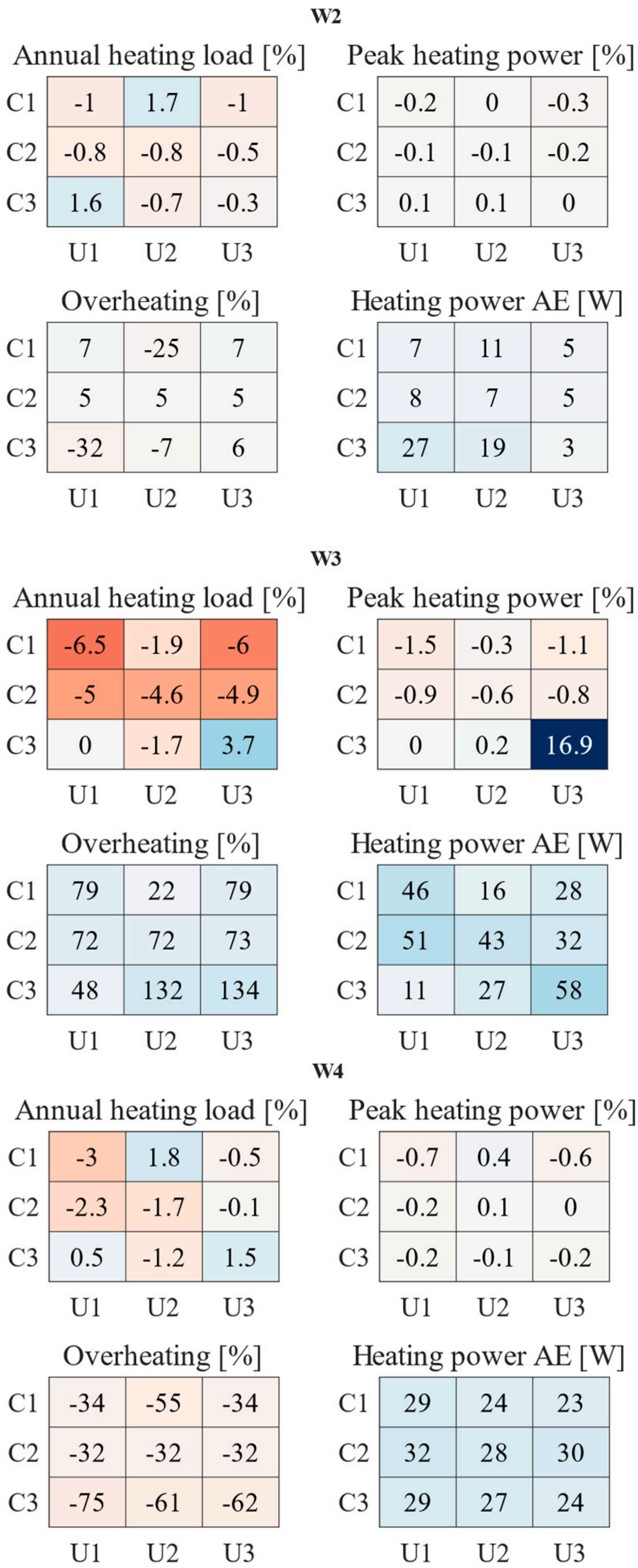

Figure 10. Distribution of error for different window LoD strategies across construction and usage profiles.

The removal of border shading (W2) results in minimal difference from the reference scenario, although the effect may be more pronounced without eaves shading (R1), which was not assessed. Changing window distribution (W3), specifically consolidating all windows on each face to a single window, has the largest effect of all strategies. W3 produces 3.8% MAE in annual heating load, 79% in overheating, and produces 35 W average error in heating power. Outside the U3C3 scenario, which is expected to produce the most variation due highly intermittent occupant behaviour and minimal insulation, W3 has little impact on peak heating load.

Unexpectedly, the lowest LoD strategy, with uniformly distributed windows (W4), has only the second most significant impact on annual heating load (1.4%), peak heating load (0.1%), and overheating (11%). Overheating was consistently underpredicted with W4, as opposed to the consistent over prediction of W3; in this case, the window–eave shading interaction instead led to greater solar gains, similar to strategy R3. Overall, this indicates that once again, window placement is a significant factor for error.

3.3. Zoning

Results for zoning LoD strategies are shown in Figures 11 and 12. Reducing the number of thermal zones reduces model functionality; so the two-zone model (Z2), reflecting occupied and unoccupied areas, cannot be used to assess the U1 scenario, and the single-zone mode (Z3) cannot be used to assess the U1 or U2 scenarios. Thus, fewer results are available for zoning than for other elements, and consequently, zoning presents lower variability compared to other strategies. Across all assessments except overheating, error increases as zoning decreases, as demonstrated with higher errors of the single-zone Z3 than the two-zone Z2. For example, annual heating energy error is 2.3% for Z2 and 3.6% for Z3; in each case, error is an underprediction. The magnitude of error generally increases with decreasing insulation (C2 and C3) and increasing intermittency of use (U2 and U3) where assessed.

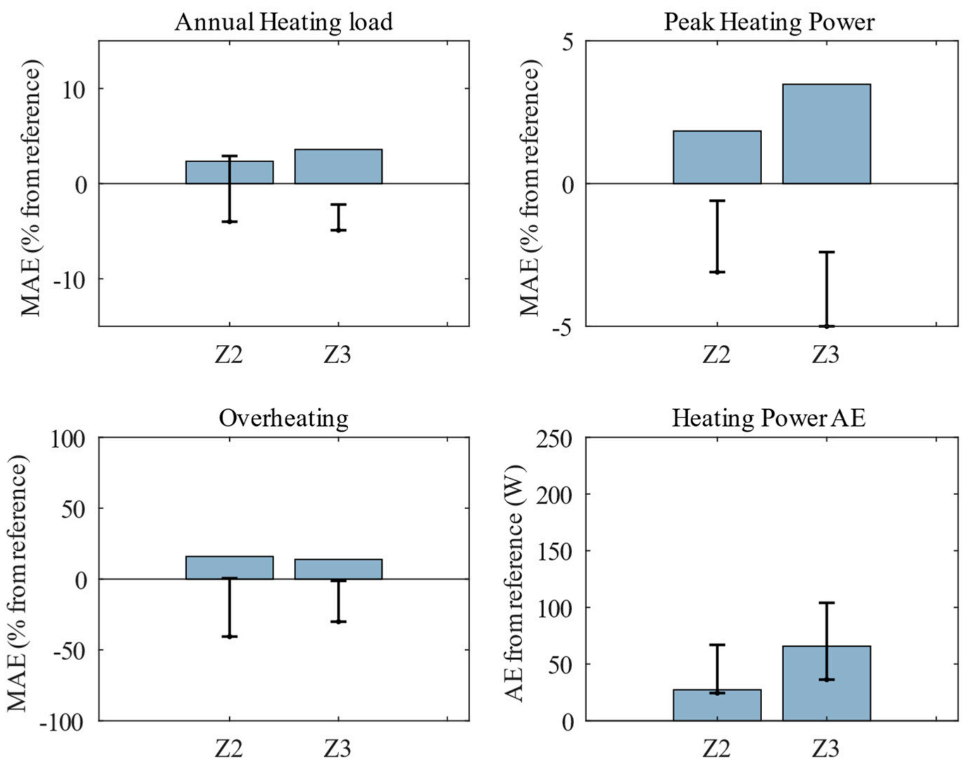

Figure 11. MAE of different zoning LoD strategies across construction and usage profiles and minimum and maximum values.

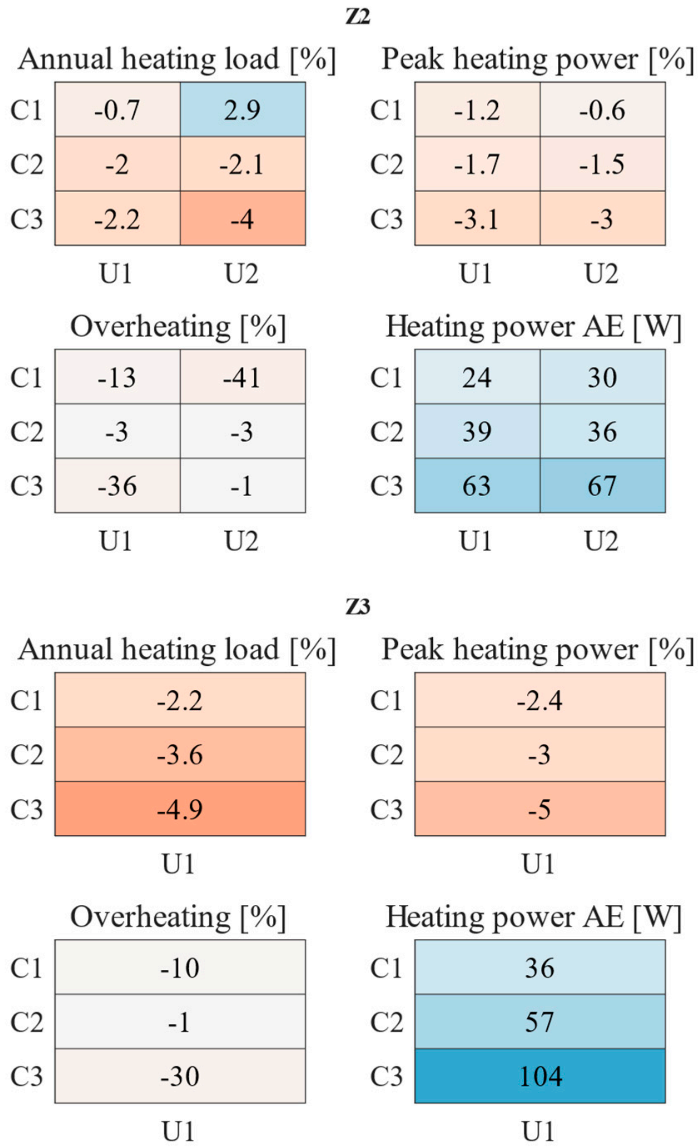

Figure 12. Distribution of error fir different zoning LoD strategies across construction and usage profiles.

3.4. Ranking of Error

LoD strategies are ranked in Table 4 according to their error in annual heating load, peak heating power, overheating, and heating power. The highest-error scenarios are R3 and Z3, the lowest-LoD representations of roof and zoning, respectively. W2, where windows are represented without border shading, produces the lowest error in all cases.

Due to the significant error exhibited for some LoD strategies were no ceiling or wall insulation is present (C2 and C3), and due to the impracticality of the combinations, some LoD results are included for only the C1 profile, where this scenario presents the least error.

The following observations can be derived from Table 4:

1. Zoning strategy has a considerable impact on peak demand and other time-sensitive results.
2. Removing the roof air volume (R2) consistently leads to moderate error across each assessment category.
3. Eaves shading (R3) and window placement (W3 and W4) both affect solar gains through windows and through the building fabric, and both introduce error in all assessment categories.

Table 4. LoD of building elements ranked according to MAE error across construction and usage profiles. In some cases, insulation has a large impact on error magnitude in all assessments, in which case the fully insulated C1 construction profile is used as a representation of overall error.

	Annual Heating Load		Peak Heating Power		Overheating		Heating Power AE (W)	
1	R3-C1	8.1%	Z3	3.5%	R3-C1	99%	Z3	66
2	W3-C1	4.8%	Z2	1.8%	W3-C1	60%	R3-C1	53
3	R2-C1	3.8%	R2-C1	1.7%	W4	46%	Z2	43
4	Z3	3.6%	R3-C1	1.5%	R2-C1	22%	R2-C1	33
5	Z2	2.3%	W3-C1	1.0%	Z2	16%	W3-C1	30
6	W4	1.4%	W4	0.3%	Z3	14%	W4	27
7	W2	1.0%	W2	0.1%	W2	11%	W2	10

4. Discussion

Representing buildings at the urban scale is a modelling-intensive task. The results of this work provide useful insights into the trade-offs between modelling representation complexity and model accuracy for various building LoD strategies for BEM and UBEM, with the impacts on accuracy available for reference in Figures 7–12 and Table 4, thus assisting UBEM modellers by directing modelling effort towards areas with the greatest impact for the outcomes of interest.

This work assesses the magnitude of different LoD strategies against a range of useful assessments and across a combination of common insulation levels and heating behaviours. Assessments used in this work include peak demand and time-series heating power error, which are not often assessed in similar works but are highly important, as accurately quantifying temporal effects is increasingly important for optimising network infrastructure, integrating intermittent renewable energies, such as solar PV, and implementing energy demand response [31]. Additionally, this work includes a range of usage behaviours and construction profiles to ensure that the results reflect the range of behaviours and insulation levels observed.

4.1. Roof

The results indicate that modelling the roof attic is highly impactful where ceiling insulation is not present. Conversely, where ceiling insulation is present, a more common occurrence, the impact of roof LoD on error is modest and ubiquitous across all assessments. Accurate representation of the roof volume requires significant modelling effort, which is important in the non-insulated case but can likely be avoided where ceiling insulation is present.

Removal of eaves shading ($R3_{C1}$) led to the largest errors in annual heating load (8.1%) and overheating (99%), highlighting the significance of shading and the need for accurate shading representations. The modelling of eaves shading is easily automatable and hence presents a simple measure to increase model accuracy significantly. However, eaves interact with windows; hence, window distribution should be considered together with shading devices.

4.2. Windows

The removal of the small border shades (W2) had minimal impact on all assessments; however, modelling border shading can be automated with minimal modelling effort and hence presents a simple method of decreasing error.

Accurate window distribution requires significant modelling effort to replicate the multiple geometries on numerous faces. Window distribution strategies produced mixed effects. Altering the window placement while maintaining window area on each face (W3) results in errors of significant magnitude and range. Whereas a more significant change to window placement, evenly distributing windows on all faces to a consistent W/W ratio (W4), led to both smaller errors and range. The W3 strategy accumulated windows together centrally and exposed more window area to solar radiation lower in the wall compared to

W1, W2, and W4. Hence, strategy W3 underpredicted annual heating load (−3.8%) and overpredicted overheating (11.1%).

These results indicate that shading/window interactions are key drivers of error, particularly for annual heating load, peak heating power, and overheating. Accurate modelling of window placement is essential where those assessments are critical and where there are shading sources present near windows, such as eaves, trees, and closely neighbouring buildings.

4.3. Zoning

Zoning impacts temporal assessments' peak heating power and heating power absolute error the greatest. For example, peak heating power error for Z2 ranged between −0.6% and −3.1% and error for Z3 ranged between −2.4% and −5.0%, indicating a consistent underprediction. The impact of zoning on these temporal factors is likely due to the moderating effect of larger zone air volumes, which dampen the rate of change of temperature due to external heating or cooling.

The increased error from reduced zone strategies on temporal power demand requires care when used for applications such as predicting peak loads or planning for the utilisation of intermittent resources, such as electricity from solar PV.

Single thermal zone models are commonly implemented for UBEM due to the simplicity of implementing at scale. Additionally, implementing multi-zone models require knowledge of building interior layout, which is often inaccessible to modellers, particularly at scale. Practical interior layouts may be automatically generated, or modelling approaches such as a typical buildings approach may be used to produce UBEMs with multiple interior layouts [32].

4.4. On the Accuracy of Shoebox Models

Shoebox building models can be created simply at scale and are commonly employed in UBEM [11–13]. Shoebox models typically employ single-zone extrusions of building footprints, flat roofs, no eaves, and windows described via window-to-wall area ratios, characteristics matching LoD strategies R3, W4, and Z3. Thus, the results of this work provide general conclusions which can be extrapolated to provide a qualitative assessment of shoebox models.

1. Generally, single-zone models cannot represent variations in spatial heating behaviour; therefore, the use of single zone-models is restricted in these applications.
2. Annual heating and peak heating power are significantly underestimated as the impacts of roof (R3), window (W4), and zoning (Z3) add constructively to error.
3. Overheating is overestimated due to the impact of roof LoD (R3) dominating other sources of error; however, the error is moderated as the window LoD (W4) tends to underestimate overheating.
4. All elements contribute towards time-series error; therefore, caution is advised when using shoe-box models where temporal accuracy is required.

Given these net inaccuracies, caution should be applied when using shoebox models for UBEM. The results of this work indicate that easy-to-implement increases in the LoD of building elements, such as eaves and border shades, where applicable, could be modelled to decrease the errors of shoebox models incrementally. Further increases in accuracy would be available by mimicking real window placement and adding internal zoning; however, the practical implementation of these techniques is restricted by data and automation limitations.

4.5. Limitations

In this work, the isolated error of individual LoD elements were assessed. This approach does not capture the interaction between different LoD elements. For example, the combined effects of window eaves and window LoD strategies could affect solar gain into buildings, but the interactions between these elements were not explored. Additionally, the interactions between windows and zoning, and roofs and zoning were not explored. These interactions may be significant and present an area of future work.

This work used a stand-alone single-storied family home. Multiple different types of buildings exist, such as multi-storey buildings and joined apartment buildings. The relative magnitude of results for assessments can change for different building types, so exploring the impacts of different building types presents another opportunity for future work.

The location for this analysis is Christchurch, New Zealand, and the relative magnitude of results may shift depending on location and weather type. While these results, and particularly the overall trends, are likely generalisable for New Zealand itself, future work can conduct these assessments in multiple locations for regionally specific values. Similarly, the primary interest for New Zealand, due to its climate, is heating [33]. However, in other locations, cooling may be of more importance, and the magnitude of error for different LoD elements, such as window placements and eaves, may be greater for cooling than for heating. Thus, the effects of LoD strategies on cooling error should be explored for regions where cooling is of greater interest. Further analyses in locations with different climates would also provide additional context for the results presented in this work and further inform modellers on the appropriate selection of LoD elements.

This work demonstrates the importance of solar shading in producing error in BEM models; however, it limited its analysis to the building. External causes of shading may have equal or greater importance. For example: garages, roads, fences, and neighbouring buildings can change the solar shading and reflected radiations. An additional analysis exploring the impacts of the LoD of various surrounding elements would present useful information for UBEM. Such an analysis would help us to determine which external elements are most important to include in models.

A sensitivity analysis was not conducted in this work. However, a comprehensive range of scenarios was assessed, which capture a broad range of potential model inputs. Table 3 shows the scenarios modelled in this work, covering the 63 relevant combinations of LoD strategies and model inputs, and the addition of sensitivity analyses alongside these scenarios would be prohibitively computationally expensive. Additionally, the use of scenario analyses instead of sensitivity analyses matches the approach of previous work assessing the effect of LoD strategies on model accuracy [24,25].

5. Conclusions

The impacts of LoD strategies for roof, window, and zoning elements are assessed according to a comprehensive range of outputs: annual heating load, peak heating demand, overheating, and time-series heating error. These assessments are conducted across a range of practical building constructions and usage behaviours to provide results for a range of realistic conditions in a representative New Zealand house. Overall, reducing the LoD of model elements increases model error, but the magnitude of these increases depends on the element in question. Removal of the roof volume (scenarios R2 and R3) introduces ubiquitous error across all assessments, with mean absolute error ranging from 1.5% for peak heating power to 99% for overheating. The importance of interactions between windows and shading is shown, as both affect solar thermal gains; and reducing the LoD of windows and/or shading elements, such as eaves, can greatly reduce the overall model accuracy. The reduced LoD of internal zoning has the greatest effect on time-series heating power (mean absolute error of 66 W for Z3) as changes in the internal air volume affect the rate of change of air temperature, thus reducing temporal accuracy. These results suggest that shoebox models of the type commonly employed for large-scale UBEMs produce considerable error, which is biased towards the underestimation of annual heating load and peak power and the overestimation of overheating, so these will not cancel each other out at scale. The inclusion of eave shading and window border shading can be automated with little additional modelling effort, so this provides an easy-to-implement means of obtaining modest increases in model accuracy. Conversely, while accurate representations of window size and placement and accurate internal zoning models provide the means of increasing model accuracy considerably, the implementation of these improvements is limited due to data availability and automation barriers.

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Appendix A

Fixed inputs, occupancy, and plug load gains and schedules are detailed in Tables A1 and A2, respectively.

Table A1. Building construction for the nominal building insulated to profile.

	Category	Level
Occupant gains	Occupancy density (people/m^2)	0.031
	Occupants number	4
	Metabolic rate per person (W/person)	100
Plug load gains	Equipment's gain power density (W/m^2)	24.5

Table A2. Occupancy and plug load schedules.

Schedule Type	Days	00:00–08:00	08:00–11:00	11:00–18:00	18:00–22:00	22:00–24:00
Occupancy	Weekdays	1	0.6	0.6	1	1
	Weekends and holidays	1	1	0.5	0.7	1
Plug	All days	0.03	0.23	0.23	0.27	0.2

Nominal building construction is shown in Tables A3–A5 to match the C1 profile, where only external wall and ceiling constructions differ between profiles.

Table A3. Building constructions for the nominal building insulated to profile C1.

Surface	Layers (Outer-to-Inner)	Thickness (m)	Thermal Conductivity (W/m·k)	Specific Heat (J/kg·K)
External wall	Brick	0.07	0.6	840
	Air gap	0.05	0.0262	1005
	Timber frame	0.0126	0.14	1400
	Wall insulation	0.0452	0.04	840
	Timber frame	0.0126	0.14	1400
	Plasterboard	0.01	0.17	1090
Internal partition	Plasterboard	0.01	0.17	1090
	Timber frame	0.0126	0.14	1400
	Cavity	0.0012	0.0262	1005
	Timber frame	0.0126	0.14	1400
	Plasterboard	0.01	0.17	1090

Table A3. *Cont.*

Surface	Layers (Outer-to-Inner)	Thickness (m)	Thermal Conductivity (W/m·k)	Specific Heat (J/kg·K)
Ceiling	Ceiling insulation	0.09	0.04	840
	Timber frame	0.0126	0.14	1400
	Ceiling insulation	0.0577	0.04	840
	Timber frame	0.0126	0.14	1400
	Plasterboard	0.013	0.17	1090
Roof	Corrugated iron	0.002	52	449
Floor	Ground	0.0422	0.04	840
	Sandstone	0.015	0.2	710
	Concrete	0.0226	1.4	1000
	EPS foam	0.018	0.03	1400
	Concrete	0.0226	1.4	1000
	Mixed concrete (2% steel)	0.085	2.5	880

Table A4. Window constructions.

	Layers (Outer-to-Inner)	Thickness (m)	Thermal Conductivity (W/m·k)
Glazing	Generic clear glass	0.0422	0.04
	air	0.015	0.2
	Generic glear glass	0.0226	1.4

Table A5. Window aggregate thermal characteristics.

	Total SHGC	R-Value (m^2K/W)
Glazing	0.74	0.37

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