

Article

Evaluation of Steady-State Volumetric Heating Load Methods Considering Building Envelope Type and Window-to-Wall Ratio

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Abstract

Recent studies have shown that building-envelope characteristics, including thermal mass and window-related solar gains, can significantly influence heating load behavior. However, their implications for the applicability and accuracy of simplified volumetric heating load methods remain insufficiently understood. Therefore, this study evaluates the applicability and accuracy of steady-state volumetric heating load methods under varying envelope conditions. Representative residential building models with different envelope types and window-to-wall ratios (WWRs) were analyzed. Heating loads were calculated using a normative volumetric approach based on tabulated specific heat-loss coefficients (Method 1) and a recalculated approach incorporating envelope characteristics and solar gains (Method 2). A comparison at hourly, peak-load, seasonal, and load-duration-curve (LDC) levels revealed that the performance of steady-state volumetric methods is strongly dependent on both envelope characteristics and the level of heating load assessment. Method 1 consistently overestimated seasonal heating demand by 41–218%, whereas Method 2 substantially reduced the error. However, Method 2 still underestimated annual heating demand in highly insulated buildings (up to 39%) and peak heating load (up to 63%). These findings indicate that the applicability of volumetric methods depends on both envelope characteristics and the level of heating load assessment. The results highlight the importance of accounting for envelope-dependent thermal-mass effects when applying volumetric methods to hourly, peak-load, seasonal, and LDC-based analyses.

Keywords: building heat load; steady-state method; specific heat loss; envelope type; window-to-wall ratio (WWR); district heating

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1. Introduction

In temperate and cold climates, district heating (DH) provides a more cost-effective and sustainable solution for supplying heat to buildings in urban areas [1–3]. As cities have continued to expand, the demand for DH systems has steadily increased. DH systems are typically designed based on the aggregated heat demand of connected buildings, making accurate estimation of building heating load a critical task in system planning and operation [4]. Accurate heating load estimation is essential for system capacity sizing, net-

work transmission capability, operational control strategies, and overall economic performance. Inaccuracies in heating load estimation, particularly in cold-climate regions, may result in either the oversizing or undersizing of heat sources, thereby reducing operational efficiency and increasing investment risk [5].

Estimation approaches for district heating demand are generally categorized into bottom-up and top-down methods [4]. Bottom-up approaches estimate heating demand by calculating the heat loads of individual buildings and aggregating them to the system level. These approaches are often used for newly planned district heating systems or systems without heat metering, for which operational consumption data are unavailable. In contrast, top-down approaches estimate heating demand from aggregated operational or statistical data, such as historical heat consumption and weather records. These approaches are mainly applicable to existing district heating systems in which heat consumption is measured at the building or user level.

Recent studies have increasingly adopted data-driven and machine-learning techniques for heating load prediction and forecasting. These methods have demonstrated high prediction accuracy using historical operational data, weather information, and machine learning algorithms [6,7]. Hua et al. [8] classified district heating load forecasting methods into two categories: white-box (physics-based) and black-box (data-driven) approaches.

White-box methods rely on detailed physical building parameters and simulation tools, whereas black-box models predict heat demand directly from measured operational data without explicit physical modeling. Because of their reliance on detailed building-specific inputs and expert calibration, physics-based building-level simulation approaches may have limited practical applicability for large-scale system analyses involving extensive building stocks [9,10]. Similar limitations have been reported in previous studies. Moreau et al. [11], Goy et al. [12], and Masson et al. [13] highlighted the challenges associated with obtaining detailed building-level information for large-scale energy analyses. Their studies showed that increasing the spatial resolution of building-energy assessments substantially increases data-gathering requirements and computational burden, while comprehensive building databases are rarely available at urban and regional scales. Similarly, black-box (data-driven) approaches depend on the availability of historical operational datasets, monitoring infrastructure, and representative training data, which may not be available for newly planned district heating systems or existing systems without heat metering and often require one or more heating seasons of data collection before reliable model development is possible.

Consequently, despite advances in physics-based and data-driven approaches, simplified steady-state methods remain widely used in district heating planning and capacity estimation due to their modest data requirements.

The steady-state, peak-load-based design framework is widely reflected in international engineering practice. In Europe and Nordic countries, EN 12831-1 provides the fundamental steady-state methodology for calculating building design heat loads, while national annexes refine climatic and operational parameters according to local conditions [14,15]. Building-level design loads are subsequently aggregated at the system level using diversity factors tailored to national conditions. Similar steady-state principles are adopted in China (GB 50736-2012) [16,17] and South Korea [18], where peak-load or unit-load criteria are used for equipment capacity selection and district heating approval. In Mongolia, DH design is governed by BNbD 41-02-13 [19]; in Russia, it is governed by SNiP 41-02-2003 ("Heating Networks") [20]. Both standards adopt a steady-state, peak-load-based calculation approach using normative specific heat-loss values per unit building volume and prescribed design outdoor temperatures for system connection and network sizing. Although these methods enable practical and rapid estimation of heat-source ca-

capacity and network dimensions, they do not explicitly consider building thermal mass, solar heat gains, or dynamic building thermal behavior.

Therefore, this study focuses on the steady-state volumetric method, a widely used simplified approach in cold-climate regions for architectural design and district heating system planning, and evaluates its applicability to district heating system-level analysis.

1.1. Steady-State Volumetric Method for Heating Load Calculation

The volumetric method for estimating building heating loads was originally proposed by Ermolayeva [21] for use in the early stages of architectural design and DH system planning. In this method, heating load is determined by multiplying the specific heat-loss coefficient defined per unit building volume ($W/(m^3 \cdot K)$) by the building volume and the temperature difference between the indoor and outdoor environments. The key parameter of this approach is the specific heat-loss coefficient, which considers only conductive heat losses through the building envelope.

In Russia, Kazakhstan, and Mongolia, which share similar cold climates, this method has been simplified by precalculating specific heat-loss values based on building geometry and architectural characteristics and adopting them as normative coefficients in district heating standards. In engineering practice, the appropriate coefficient is selected from the tabulated values in the standard, based on the building type and volume. Furthermore, recent studies from countries where specific heating-characteristic approaches remain embedded in engineering practice have continued to apply these approaches in building energy assessment and district heating system modeling [22,23].

In Mongolia, these normative coefficients derived from Ermolayeva's original formulation were incorporated into the Mongolian DH standard BNbD 41-02-13 and continue to be used today. However, these coefficients account only for conductive heat losses through the building envelope, assuming a fixed thermal transmittance (U -value).

Several studies have attempted to refine the specific heat-loss formulation. Ermolayeva et al. [21] proposed modifications to the original equation, Melikyan et al. [24] incorporated infiltration losses and internal heat gains, and Fouda et al. [25] examined the effect of solar radiation. Previous studies have shown that specific heating demand varies with building dimensions and geometric characteristics. Although these developments improved the representation of factors affecting building heating demand, heating load variation is still represented primarily by the indoor–outdoor temperature difference, while the normative specific heat-loss coefficient remains fixed for a given building category.

Consequently, the influence of building-envelope characteristics, particularly thermal mass, on the accuracy and seasonal performance of volumetric heating load calculations has not been systematically evaluated.

1.2. Evolution of Building Insulation Standards and Research Gap

Building insulation standards have become progressively more stringent in many cold-climate countries over recent decades, resulting in substantial reductions in envelope U -values [26]. Building insulation standards have improved over time, resulting in a significant lowering of envelope U -values. In Mongolia, the shift from BNbD 2.01-03-1992 to BNbD 25-01-2020 [27] strengthened insulation requirements. Compared with those of benchmark buildings constructed in 1992, the 2020 standard reduced U -values in Ulaanbaatar by approximately 61% for external walls, 49% for floors, 60% for ceilings, and 33% for windows, as illustrated in Figure 1. The revisions in insulation standards are summarized in Table 1. Following the major revision introduced in 1997, insulation requirements for walls, ceilings, and floors have remained relatively stable, whereas those for windows have gradually become more stringent.

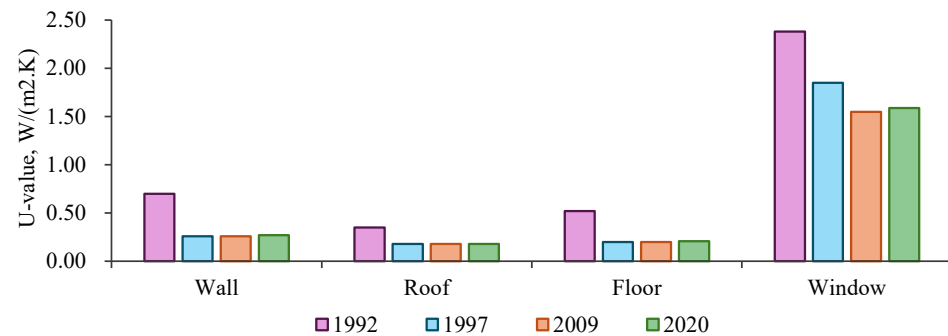


Figure 1. Evolution of U-value requirements in the Mongolian Building Insulation Standard.

Table 1. Thermal transmittance values of building envelopes ($W \cdot m^{-2} \cdot K^{-1}$).

	BNbD 2.01-03-1992	BNbD 2.01-03-1997	BNbD 23-02-2009	BNbD 25-01-2020
U_{wall}	0.7	0.26	0.26	0.27
U_{Floor}	0.35	0.18	0.18	0.18
$U_{ceiling}$	0.52	0.2	0.2	0.21
U_{window}	2.38	1.85	1.55	1.59

In parallel, the influence of thermal mass on building thermal behavior has been extensively investigated. Previous studies have shown that thermal mass affects heat storage and release processes, indoor temperature fluctuations, and building energy demand [28–30]. Recent studies have further demonstrated that thermal mass interacts with window performance and window-to-wall ratio (WWR), significantly influencing building thermal performance [29].

Despite these developments, many building standards and simplified engineering calculations continue to represent heating demand primarily using steady-state heat transfer and envelope U-values, with limited consideration of thermal-mass effects [28,30].

As insulation levels improve, heating load behavior becomes increasingly sensitive to the window-to-wall ratio (WWR) because of the effects of solar gains and building thermal mass [30,31]. In contrast, the volumetric method adopted in district heating standards represents heating load variation mainly through changes in outdoor air temperature while maintaining a fixed normative specific heat-loss coefficient for a given building category.

Consequently, although the effects of thermal mass, solar gains, and window characteristics on building thermal performance have been widely investigated, limited attention has been given to how these factors influence the accuracy and applicability of simplified volumetric heating load methods. In particular, their influence on the applicability and accuracy of volumetric heating load methods in buildings constructed under contemporary insulation standards remains unclear.

This study contributes to the literature by systematically evaluating the applicability of steady-state volumetric heating load methods under varying envelope conditions and by demonstrating how insulation level, WWR, and envelope-related dynamic characteristics affect their accuracy in district-heating applications.

Therefore, this study aims to evaluate the applicability, accuracy, and limitations of the steady-state volumetric method under varying building-envelope conditions by comparing its predictions with dynamic simulation results. Particular attention is given to the influence of insulation level, envelope type, and window-to-wall ratio on the accuracy of heating load estimation.

2. Methodology

A simplified single-zone residential model was adopted to evaluate the effects of building envelope type and WWR on heating load estimation. Three envelopes were considered, and five WWR scenarios ranging from 10% to 30% were examined with each envelope, resulting in a total of 15 cases. Heating loads obtained from normative, steady-state-based methods were analyzed for all cases. The cases represent typical residential buildings under different insulation standards.

Heating loads were calculated using two simplified approaches. Method 1 was based on the tabulated normative specific heat-loss values prescribed in the Mongolian district heating (DH) standard; in Method 2, the normative coefficient was recalculated for each case using the extended formulation proposed by Fouda et al. [25], incorporating building geometry, envelope thermal properties, and solar radiation effects. Results from both methods were benchmarked against a dynamic simulation performed using the Thermal Environmental Performance Simulator for Heat, Air, and Moisture (THERB for HAM). The analysis focused on peak heating load, hourly load, monthly consumption, and annual heating demand, reflecting typical design and operational metrics in DH systems.

Consistent boundary conditions were applied across all methods using meteorological data for Ulaanbaatar in 2020, and the indoor air temperature was maintained at 20 °C in all models. To ensure methodological consistency, the same hourly outdoor air temperature data used in THERB for HAM were also applied in Method 1 and Method 2. Because Method 1 does not account for mechanical ventilation or internal heat gains (e.g., occupants, equipment, and lighting) in residential buildings, these factors were likewise excluded from Method 2 and the dynamic simulation. Internal gains were excluded to isolate envelope-related effects. To represent the background natural air exchange in mechanically unventilated dwellings, a constant infiltration rate of 0.3 ac/h was applied in THERB for HAM. This value was held constant across all cases and was not treated as a study variable, since steady-state volumetric methods do not explicitly account for infiltration as a separate physical process. Incident solar radiation on building surfaces was obtained from the dynamic simulation and used as input for Method 2 calculations.

2.1. Building Models

To compare normative methods with dynamic simulation under consistent conditions, three representative single-family residential building envelope models were defined. Model 1 corresponds to pre-1990 housing, whereas Models 2 and 3 represent post-1990 buildings with improved insulation. Envelope types and WWR scenarios were examined together in this study.

2.1.1. Building Geometry and WWR

A simplified single-family residential model (6 m × 9 m plan, height 2.4 m; floor area 54 m²) was adopted to isolate methodological differences.

In the normative specific heat loss value, the Mongolian DH standard assumes a fixed WWR of 18%, inherited from earlier Russian construction norms under which the WWR was limited based on window thermal performance [32]. As a result, WWR variability is not explicitly reflected in the tabulated normative heat-loss values. However, in practice, WWR varies considerably across residential buildings and directly influences heating demand and associated energy costs [33,34].

To examine whether the fixed WWR assumption embedded in the DH standard remains appropriate under contemporary building conditions and evaluate the capability of Method 2 to capture this effect, five WWR scenarios ranging from 10% to 30% were considered. In all scenarios, fixed 1.5 m × 1.5 m windows were assumed on the east and

west facades, and the prescribed variations were applied exclusively to the south-facing facade. This configuration emphasizes solar gains under representative exposure conditions. The geometric configuration and window-area variations are illustrated in Figure 2, and the envelope construction types are shown in Figure 3.

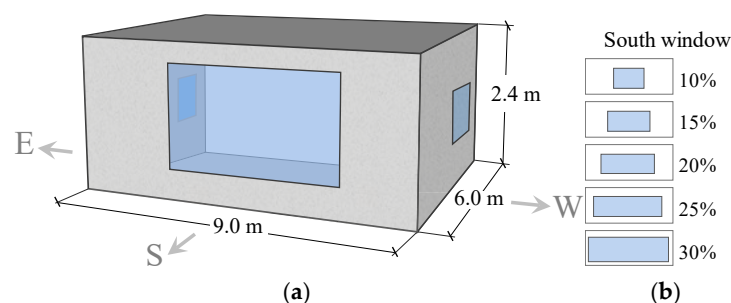


Figure 2. Simplified residential building model and WWR configurations: (a) building model; (b) WWR types.

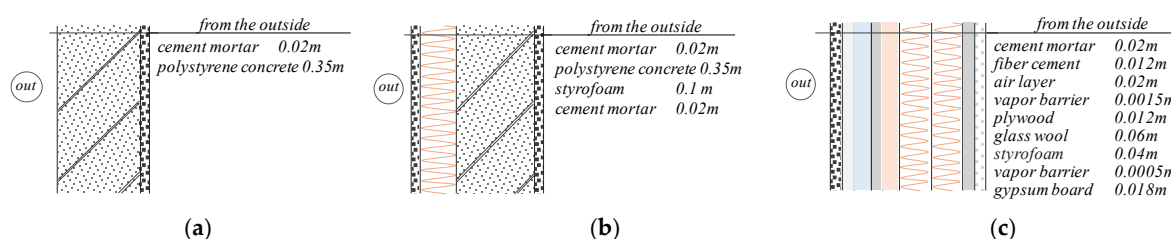


Figure 3. Envelope wall types used in the building models: (a) Model 1: concrete wall; (b) Model 2: insulated concrete wall; (c) Model 3: insulated wood-framed wall.

The geometric properties under the different WWR scenarios are summarized in Table 2.

Table 2. Geometric properties of the building model.

Model	Unit	Window to Wall Ratio (WWR)				
		10%	15%	20%	25%	30%
Wall area	m ²	64.8	61.2	57.4	54	50.4
Total window area	m ²	7.2	10.8	14.4	18	21.6
Building height	m	2.4				
Roof and base area	m ²	54				
Building perimeter	m	24				
Building volume	m ³	129.6				

2.1.2. Building Envelope

The three building envelope models were selected to represent typical residential construction practices before and after the implementation of updated insulation standards. Envelope layer compositions and thermophysical properties were defined for each model and used as inputs for Method 2 and the dynamic simulation. The corresponding wall construction typologies are illustrated in Figure 3.

The envelope thermal transmittance values (U-values) are summarized in Table 3. Model 1 represents a pre-1990 heavyweight concrete envelope designed according to earlier thermal standards, whereas Models 2 and 3 represent contemporary envelopes designed in accordance with BNbD 25-01-20. Model 2 is a heavyweight insulated envelope, whereas Model 3 is a lightweight insulated envelope. Models 2 and 3 were assigned iden-

tical U-values but different structural masses, enabling the influence of thermal mass to be examined independently of insulation performance.

Table 3. Comparison of the U-values of the envelope for each model.

Envelope Type	U-Values ($W \cdot m^{-2} \cdot K^{-1}$)			
	Wall	Roof	Floor	Window
Model 1	1.227	0.268	1.064	1.107
Model 2	0.272	0.204	0.176	0.61
Model 3	0.272	0.204	0.176	0.61

The detailed thermophysical properties of the envelope materials for each building model are presented in Appendix A.

2.2. Calculation Method

This study adopted a three-tier methodological framework to evaluate the applicability of the steady-state volumetric heating load method under contemporary building envelope conditions. This framework enables systematic comparisons among the normative implementation, the recalculated formulation, and physically based dynamic simulation results. Method 1 represents current engineering practice, in which the specific heat-loss coefficient is selected directly from tabulated normative values provided in the Mongolian DH standard. Method 2 recalculates the coefficient for each case using model-specific geometric parameters, envelope thermal properties, and solar radiation terms based on the extended formulation proposed by Fouda et al. [25]. Dynamic building energy simulation was utilized as a reference approach. This framework enables systematic comparisons between normative implementation, recalculated formulation, and physically based dynamic simulation results.

The research framework and methodology adopted in this study are illustrated in Figure 4.

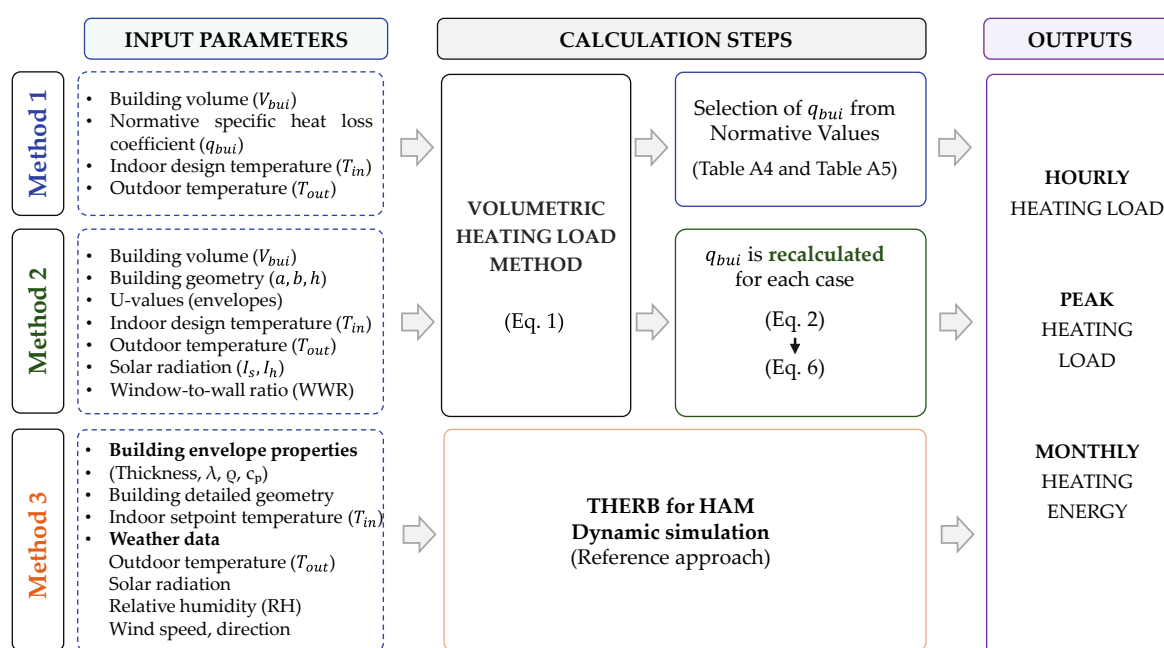


Figure 4. Research framework for the evaluation of heating load calculation methods.

The building heating load was expressed in its volumetric form as follows:

$$Q_{bui} = q_{bui} \cdot V_{bui} \cdot (t_{in} - t_{out}) \quad (1)$$

where Q_{bui} is the building heating load (W), q_{bui} is the specific heat-loss coefficient ($W \cdot m^{-3} \cdot K^{-1}$), V_{bui} is the volume of the building (m^3), and t_{out} and t_{in} are the outdoor and indoor air temperatures ($^{\circ}C$), respectively.

Equation (1) forms the basis of both Method 1 and Method 2, with the only difference being the determination of the specific heat-loss coefficient q_{bui} . In Method 1, q_{bui} is selected from tabulated normative values provided in the DH standard. In Method 2, q_{bui} is recalculated for each case using the improved formulation proposed by Fouda et al., and the resulting values are evaluated through comparison with dynamic simulation outputs.

2.2.1. Method 1: Standard-Based Normative Value Approach

In Method 1, the specific heat-loss coefficient q_{bui} is selected directly from tabulated normative values provided in existing design standards, without any recalculation of the value based on building geometry or envelope properties. This approach reflects current DH design practice in Mongolia, where heating loads are commonly estimated using tabulated normative coefficients specified in national standards.

In Mongolia, the national district heating standard (BNbD 41-02-13) recommends adopting Russian normative values for buildings constructed before 1990, whereas post-1990 buildings are evaluated directly under BNbD 41-02-13. Accordingly, Model 1 (pre-1990 single-family housing) adopts a specific heat-loss coefficient of $1.07 W \cdot m^{-3} \cdot K^{-1}$ from Russian normative data. Since the reference building volume ($129.6 m^3$) does not exactly match any category in the normative table, the value corresponding to the nearest volume category ($\sim 100 m^3$) was selected, as summarized in Table A4 of Appendix B [35]. Models 2 and 3 (post-1990 single-family housing) follow BNbD 41-02-13. Since the reference building floor area ($54 m^2$) does not exactly match any category in the standard table, the value of $0.579 W \cdot m^{-3} \cdot K^{-1}$ corresponding to the nearest floor-area category ($\sim 50 m^2$) was selected, as summarized in Table A5 of Appendix B [19].

2.2.2. Method 2: Model-Based Specific Heat-Loss Calculation

In Method 2, the extended formulation proposed by Fouda et al. [25] was adopted to investigate the physical basis of the normative heating load method. This formulation is based on Ermolayeva's specific heat-loss formulation [36], which forms the basis of the normative specific heat-loss coefficients adopted in the DH standard. By incorporating solar heat gains into the original formulation, the extended model enables specific heating loads to be estimated while accounting for solar gains.

Accordingly, the specific heating load considering solar gains was calculated as follows:

$$q_{hg} = q_{bui} \cdot (t_{in} - t_{out}) - q_{sol} \quad (2)$$

where q_{hg} is the specific heating load considering solar gains ($W \cdot m^{-3}$), q_{bui} is the specific heat loss obtained from Equation (3) ($W \cdot m^{-3} \cdot K^{-1}$), and q_{sol} represents the solar heat gain per building volume ($W \cdot m^{-3}$).

The specific heat-loss coefficient q_{bui} was then calculated using Ermolayeva's formulation:

$$q_{bui} = \left[2U_{wall} \left(\frac{1 - \mu_{wd}}{b} + \frac{1}{a} \right) + \frac{U_{ce}}{h} + \frac{2\mu_{wd}}{b} U_{wd} \right] \quad (3)$$

where a , b , and h represent building length, width, and height (m), respectively; μ_{wd} is WWR ($\mu_{wd} = \frac{\text{window area}}{\text{total wall area}}$); and U_{wall} , U_{wd} , and U_{ce} are the thermal transmittance of wall, window, and ceiling ($W \cdot m^{-2} \cdot K^{-1}$), respectively.

The solar heat gain was calculated as follows:

$$q_{sol} = \left[\frac{1 - \mu_{wd}}{b} U_{wall} \frac{I_s p}{\alpha_{out}} + U_{ce} \frac{I_h p}{\alpha_{out} h} + \frac{\mu_{wd}}{b} I_s n_1 n_2 n_3 \beta \right] \quad (4)$$

where I_s and I_h are the intensity of solar radiation on the surfaces of the south wall and ceiling ($W \cdot m^{-2}$); p is the rate of solar radiation absorption by surfaces of the south wall and ceiling, which is 0.4 for Models 1, 2, and 3; n_1 , n_2 , and n_3 represent the rates of reduction in radiation heat gains, which are $n_1 = 1$ (south facing), $n_2 = 1$ (impact of window frame), and $n_3 = 1$ (dust); and $\beta = 1.0$, which is the rate of the inside curtain effect. Hourly horizontal solar radiation I_h was obtained from the meteorological weather dataset, and solar radiation on the south-facing wall I_s was derived from I_h based on solar position and surface orientation, following the methodology proposed by Fouda [24, 25]. In addition, identical values were used for the solar heat gain reduction factors (n_1, n_2, n_3) and β in both methods to maintain consistent input conditions.

Envelope thermal transmittance values were calculated as follows:

$$U_i = \frac{1}{\frac{1}{\alpha_{in}} + \sum \frac{\delta_i}{\lambda_i} + \frac{1}{\alpha_{out}}} \quad (5)$$

where α_{out} and α_{in} are the outside and inside heat convection coefficients ($W \cdot m^{-2} \cdot K^{-1}$), with values of $\alpha_{out} = 23$ and $\alpha_{in} = 8$ [19]. δ_i is the thickness of material layers (m), and λ_i is the thermal conductivity ($W \cdot m^{-1} \cdot K^{-1}$) of each material layer.

Finally, the building heating load was obtained as follows:

$$Q_{bui} = V_{bui} \cdot q_{hg} \quad (6)$$

Equation (6) is a reformulation of Equation (1) in which the specific heating load considering solar gains, q_{hg} , is used in place of the normative specific heat-loss coefficient.

2.3. Dynamic Simulation

Dynamic building energy simulation, commonly used in building energy studies, was used as a physics-based benchmark to generate a transient reference for building heat demand, capturing heat transfer processes not captured by steady-state normative methods. Calculations associated with Methods 1 and 2 were computed independently using Equations (1)–(4) outside of the simulation environment, following the procedures specified in BNbD 41-02-13 [19] and Fouda et al. [25].

Separately, dynamic heating loads were obtained using the Thermal Environmental Performance Simulator for Heat, Air, and Moisture (THERB for HAM). It was used exclusively to resolve transient heat transfer within the building envelope and indoor air, providing hourly heating demand profiles for benchmarking purposes [37]. The software solves coupled heat and moisture transport equations and has been validated through standardized benchmark tests such as BESTEST [38].

Within THERB for HAM, heat transfer in envelope materials is governed by the transient energy balance equation:

$$\frac{\partial(C\rho T)}{\partial t} + c_{lw} j_{lw} \nabla T = \nabla \lambda \nabla T \quad (7)$$

where C and ρ are the specific heat and specific weight of the material containing water, respectively; c_{lw} , ρ_{lw} , and j_{lw} are the specific heat, specific weight, and flux of liquid phase water, respectively; and λ is the thermal conductivity.

Boundary conditions were determined using Equation (8):

$$-\lambda \frac{\partial T}{\partial n_v} = \alpha_c (T_a - T_s) + q_{sr} + q_{lr} \quad (8)$$

where n_v is the normal line vector directed inward on a boundary surface, α_c is the convective heat transfer coefficient, T_a and T_s are the temperatures of the air and surface, respectively, and q_{sr} and q_{lr} are the short- and long-wave radiant heat, respectively.

2.4. Weather Data and Calculation Conditions

The study site, Ulaanbaatar, Mongolia, is one of the coldest capital cities in the world. Hourly meteorological data were analyzed to characterize the local climate conditions. Figure 5 illustrates the annual variation in key meteorological variables used in the analysis. December was the coldest month, with an average temperature of -20.2 °C and a minimum temperature of -32.7 °C, demonstrating the severe winter conditions that strongly influence district heating demand.

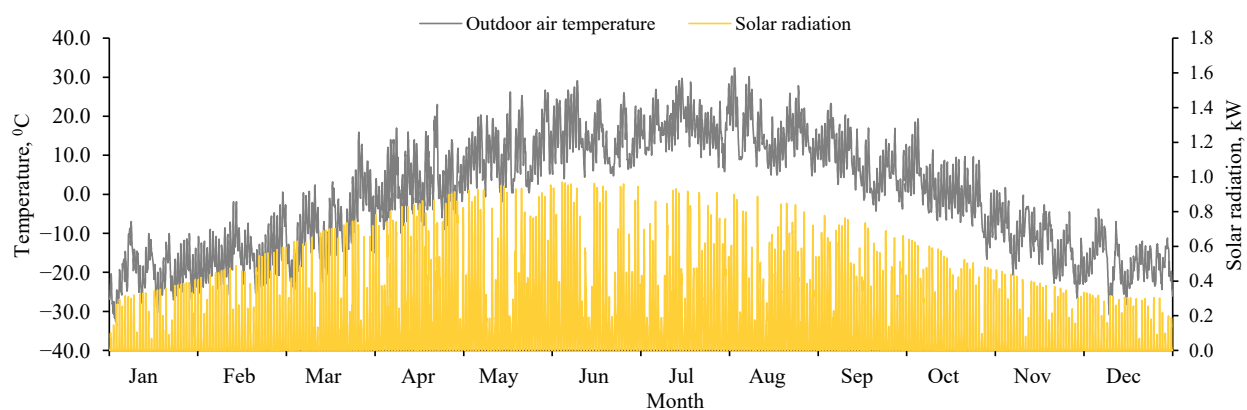


Figure 5. Meteorological indicators of Ulaanbaatar used in the simulations.

Weather data for Ulaanbaatar (47.93° N, 106.98° E; elevation 1316 m) were obtained from an IWEC (International Weather for Energy Calculations) EPW weather file [39]. The dataset includes hourly outdoor air temperature, relative humidity, solar radiation, wind speed, and wind direction. Among these variables, outdoor air temperature, relative humidity, and solar radiation were the principal climatic parameters considered in the analysis and are presented in Figure 5. The same EPW weather file was used throughout the study as the meteorological input for all analyses and simulations.

2.5. Evaluation Criteria

Relative error was used to assess bias, and the coefficient of determination (R^2) was used to quantify the overall agreement between the simplified methods and the dynamic simulation results.

Specifically, the coefficient of determination (R^2) was used to evaluate the agreement between the heating load values calculated using the steady-state volumetric method (Method 1 or Method 2) and those obtained from the dynamic simulation using THERB for HAM:

$$R^2 = 1 - \frac{\sum (A_i - Y_i)^2}{\sum (A_i - \bar{A})^2} \quad (9)$$

where A_i is the observed value (THERB for HAM results), Y_i is the predicted value (Method 1 or Method 2), and $\bar{A}$ is the mean of the observed values (mean of THERB for

HAM results). R^2 , which ranges from 0 to 1, reflects the quality of fit between the predicted and observed values.

The relative error (RE) was calculated as follows:

$$RE = \frac{Y_i - A_i}{A_i} \quad (10)$$

Finally, the mean absolute error (MAE) was used to quantify the average deviation between the heating loads predicted by the simplified methods and those obtained from the dynamic simulation:

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i| \quad (11)$$

where N is the number of samples.

3. Results

Heating load calculations were compared across 15 cases (three envelope models $\times$ five window-to-wall ratio (WWR) scenarios) using the common weather dataset described in Section 2.2. In district heating practice, the volumetric method is commonly used under data-limited conditions to estimate hourly heating loads, determine peak load for system sizing, calculate seasonal energy demand, and represent load distribution with load duration curves (LDCs). Accordingly, the results are presented in four sections.

3.1. Hourly Heating Load

Hourly heating loads during the heating season (October 1–April 30) were calculated using dynamic simulation with THERB for HAM and two simplified methods (Method 1 and Method 2). To illustrate the hourly variation in heating loads, a representative period from January 1 to January 14, corresponding to the coldest conditions of the heating season, was selected. The results are presented in Figures 6 and 7.

The dynamic reference results shown in Figure 6 indicate that both the envelope type and WWR influence hourly heating load behavior. For example, Model 1 exhibited larger load fluctuations at WWR = 30%, whereas Model 2 occasionally reached 0 kW during some hours under WWR = 25–30% conditions. In addition, although Model 2 and Model 3 have identical U-values, they exhibit different dynamic responses due to differences in thermal mass. Different heating load behavior was observed between the models despite identical U-values. This result demonstrates that thermal mass significantly affects heating load dynamics even with identical U-values, highlighting a limitation of simplified methods that rely solely on transmission parameters.

For Method 1, the hourly heating load generally followed an inverse relationship with outdoor air temperature and showed limited ability to represent the influence of envelope type and WWR on hourly heating load behavior (Figure 7a). This behavior occurs because the Mongolian DH standard defines the normative specific heat-loss coefficient as a fixed value that does not vary with envelope type or WWR. Consequently, Method 1 shows limited capability to represent the dynamic differences observed between Model 2 and Model 3.

In contrast, Method 2 recalculates the envelope-specific heat-loss coefficient for each case using the improved formulation proposed by Fouda et al., which incorporates the influence of solar radiation, as well as the actual U-values and WWR. As a result, the differences in heating loads between the models are more clearly reflected (Figure 7b,c).

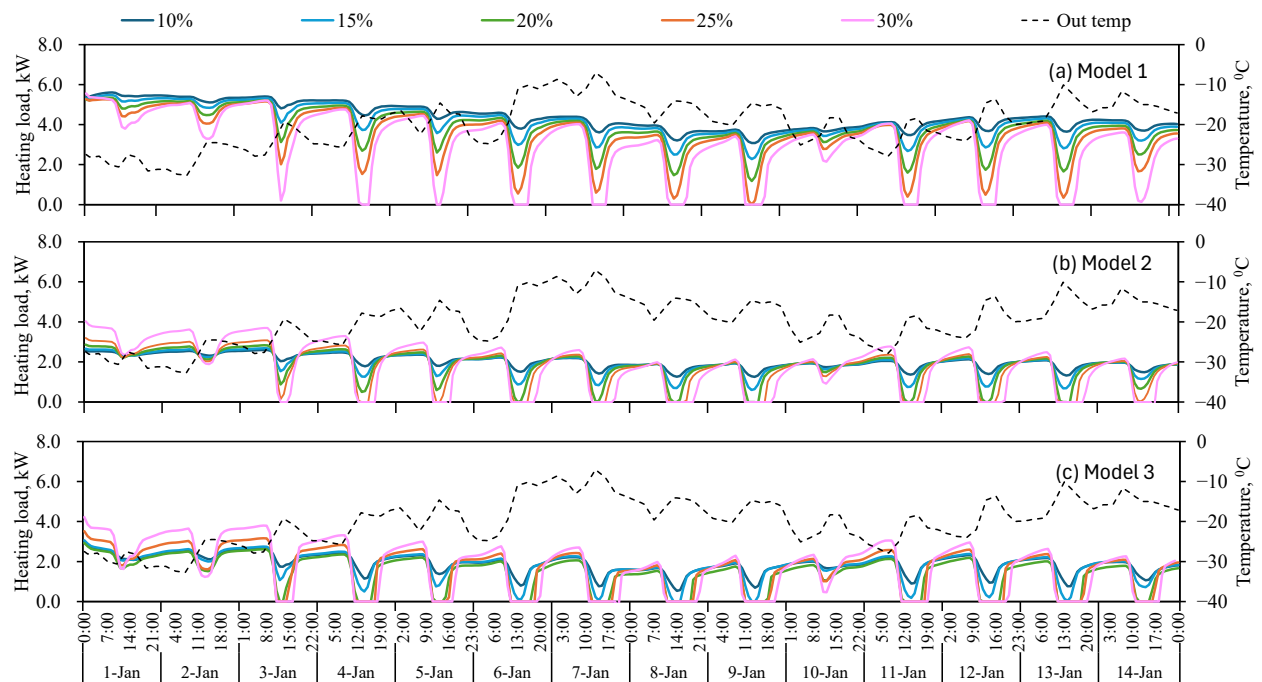


Figure 6. Hourly heating loads obtained from dynamic simulation under different window-to-wall ratio (WWR) scenarios.

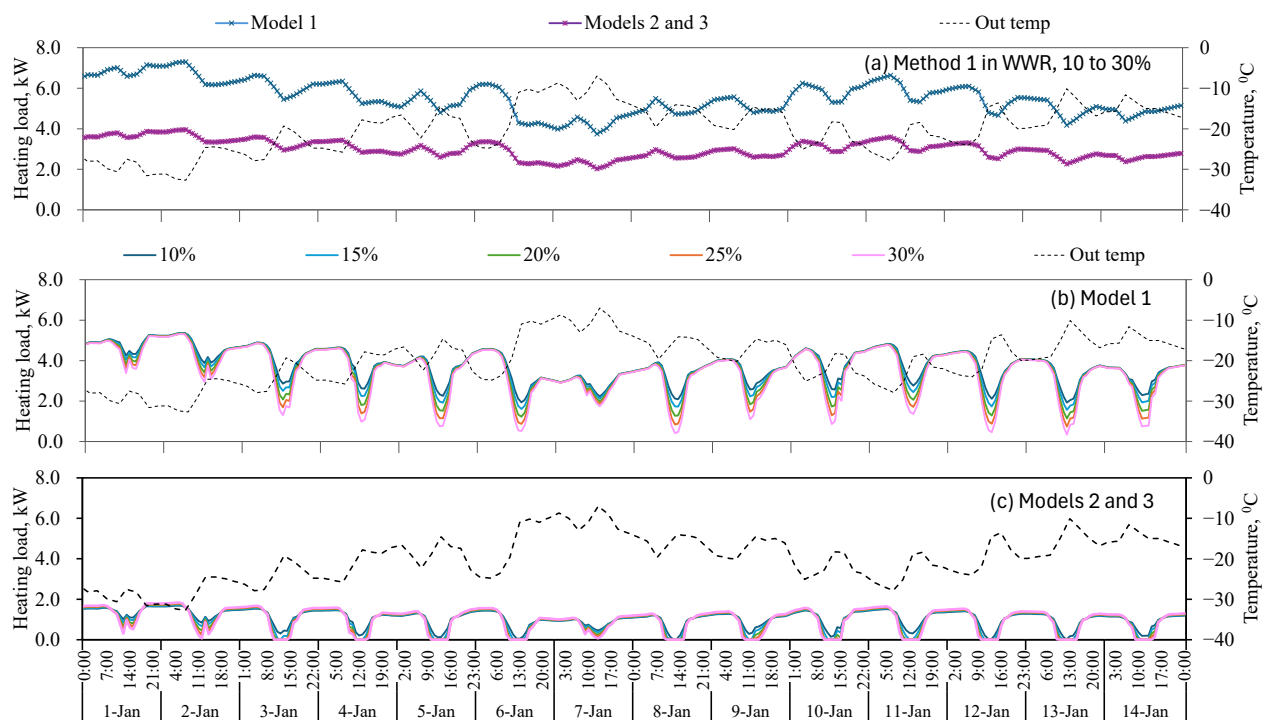


Figure 7. Hourly heating loads calculated by Method 1 and Method 2 for different models and WWR scenarios.

The performance of the simplified methods was evaluated using the mean absolute error (MAE) and the coefficient of determination (R^2), calculated using all hourly heating load values over the entire heating season, as summarized in Table 4. MAE quantifies the magnitude of the deviation from the dynamic simulation results, whereas R^2 indicates the strength of the statistical relationship between the simplified methods and the dynamic reference.

Table 4. Performance of simplified methods evaluated using mean absolute error (MAE, kW) and coefficient of determination (R^2).

Model	WWR	Method 1		Method 2	
		MAE	R^2	MAE	R^2
Model 1	10%	1.24	0.78	0.61	0.83
	15%	1.44	0.79	0.56	0.77
	20%	1.72	0.74	0.56	0.71
	25%	2.06	0.66	0.68	0.65
	30%	2.56	0.58	0.98	0.60
Model 2	10%	1.05	0.81	0.50	0.56
	15%	1.16	0.74	0.45	0.48
	20%	1.29	0.63	0.42	0.42
	25%	1.43	0.57	0.45	0.39
	30%	1.56	0.47	0.56	0.37
Model 3	10%	1.05	0.74	0.51	0.56
	15%	1.16	0.63	0.49	0.48
	20%	1.47	0.53	0.39	0.42
	25%	1.39	0.50	0.51	0.39
	30%	1.48	0.44	0.61	0.37

For Model 1, the MAE increased from 1.24 to 2.56 kW as the WWR increased from 10% to 30%, indicating that the discrepancy between Method 1 and the dynamic simulation increases with increasing WWR. In contrast, Model 2 and Model 3 showed similar MAE values in the range of 1.05–1.56 kW, suggesting that Method 1 cannot adequately distinguish the influence of envelope type and thermal mass on hourly heating loads. For Method 2, the MAE values were significantly reduced. For example, the MAE decreased from 1.05 kW to 0.5 kW for Model 2 at WWR = 10% and from 2.56 kW to 0.98 kW for Model 1 at WWR = 30%. This improvement indicates that recalculating the envelope-specific heat-loss coefficient substantially reduces the discrepancy between the simplified method and the dynamic simulation by accounting for envelope characteristics and solar gains.

The R^2 values presented in Table 4 further confirm this trend. At WWR = 10%, the R^2 values ranged from 0.74 to 0.81 for Method 1 and from 0.56 to 0.83 for Method 2, indicating a relatively strong correlation with the dynamic simulation. However, for Models 2 and 3, the correlation gradually decreased as the WWR increased, with R^2 values declining from approximately 0.56 at WWR = 10% to 0.37 at WWR = 30%. This trend suggests that although Method 2 reduces the magnitude of the error, simplified steady-state formulations still struggle to reproduce the temporal variation in heating loads under higher solar gains and larger window areas. As the WWR increased, solar gains became more influential, causing greater short-term fluctuations in the dynamic simulation results. Because these dynamic effects are not fully represented in the steady-state formulation, agreement with the dynamic simulation decreased. Consequently, Method 2 can reasonably estimate the magnitude of heating demand but cannot fully reproduce the timing and temporal variability captured by the dynamic simulation.

Overall, these results indicate that Method 1 shows limited sensitivity to variations in envelope type and does not explicitly account for changes in WWR, whereas Method 2 better captures their effects by recalculating the envelope coefficient for each case. Nevertheless, the MAE and R^2 values indicate that short-term hourly variations are not fully represented by the simplified steady-state formulation. In addition, improved insulation increases the relative influence of window size, making the WWR a more important factor in hourly heating load variation than in the poorly insulated Model 1, highlighting the increasing importance of solar gains and glazing area in highly insulated buildings. Over-

all, these results indicate that the accuracy of steady-state methods is strongly dependent on building configuration and operating conditions rather than being uniform across cases.

3.2. Peak Heating Load

Accurate estimation of peak heating load is essential in district heating (DH) system design because it determines the required capacities of heat production units and distribution equipment, as well as pipeline sizes. The peak heating loads obtained from the dynamic simulation and the simplified methods were therefore compared for different envelope models and WWR conditions.

The dynamic simulation results showed that the peak heating load generally increased as the WWR increased across all models (Figure 8). In Model 1, the peak load increased from 5.69 kW at WWR = 10% to 6.35 kW at WWR = 30%. Similar trends were observed in Models 2 and 3, where the peak loads rose from 2.89 to 4.53 kW and from 3.40 to 4.91 kW, respectively. Although these two models have identical U-values, differences in thermal mass resulted in different peak-load responses. At WWR = 10–30%, Model 3 exhibited peak loads approximately 4–31% higher than those of Model 2.

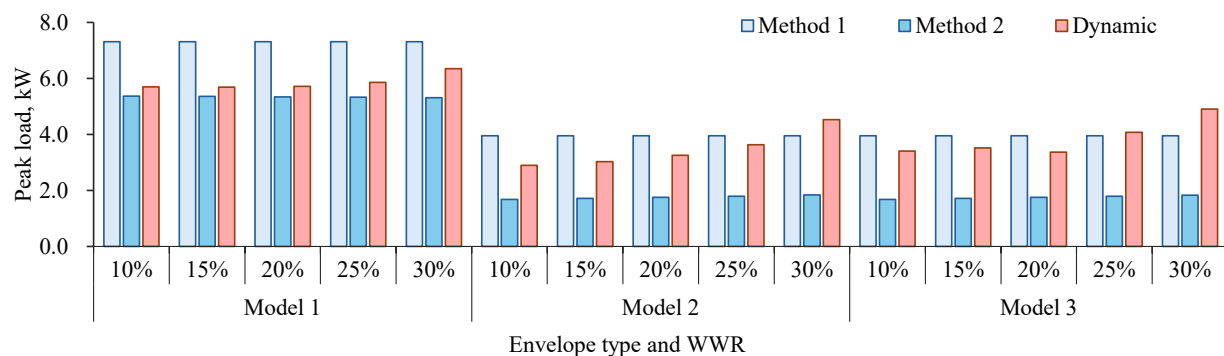


Figure 8. Comparison of peak heating load calculated using Method 1, Method 2, and dynamic simulation.

Figure 9 presents the relative errors of the peak heating load for different envelope types. Method 1 exhibited distinct error patterns across envelope models. For Model 1, the peak heating load was consistently overestimated, with relative errors ranging from 15.1% to 28.5%. Models 2 and 3 showed overestimation at WWR = 10–25%, with relative errors ranging from −3.2% to 36.8%, whereas at WWR = 30%, the peak load was underestimated, with relative errors of −12.7% for Model 2 and −19.4% for Model 3. This behavior reflects the use of fixed normative heat-loss coefficients in Method 1, which do not account for variations in WWR, solar gains, or glazing-related effects. In contrast, Method 2 consistently underestimated the peak heating load, with relative errors ranging from −5.7% to −62.6%. This systematic underestimation indicates that accounting for solar radiation alone is insufficient for accurate peak-load prediction.

Overall, the results indicate that the accuracy of Method 1 depends strongly on the selected normative heat-loss coefficient, resulting in both overestimation and underestimation of peak heating loads. In contrast, Method 2 incorporates solar radiation effects through the recalculation of the specific heat-loss coefficient; however, its ability to improve peak-load estimation remains limited. The increasing underestimation observed with increasing WWR suggests that peak-load conditions cannot be adequately represented by a steady-state treatment of solar gains alone. Instead, peak heating loads are also influenced by thermal mass and thermal inertia, particularly in highly insulated

buildings. Consequently, refining the volumetric method by incorporating solar radiation effects alone may still result in substantial underestimation of peak heating loads.

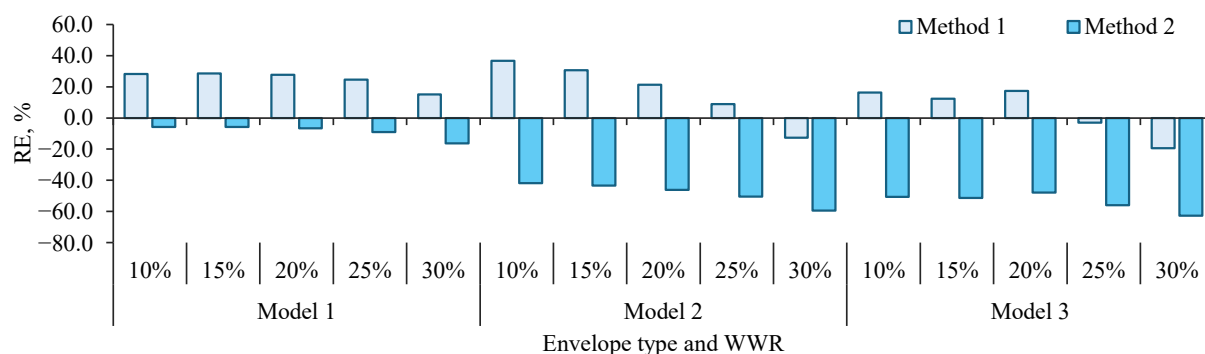


Figure 9. Relative error (%) of peak heating load for different envelope types.

The relationship between the peak heating load and the heating load corresponding to the minimum outdoor temperature is shown in Figure 10. According to the DH standard, the peak heating load is assumed to occur at the lowest outdoor temperature of the coldest month. However, the dynamic simulation results showed that the peak load did not necessarily coincide with the minimum outdoor temperature. Therefore, for each case, the heating load at the minimum outdoor temperature was compared with the actual peak heating load from the dynamic simulation.

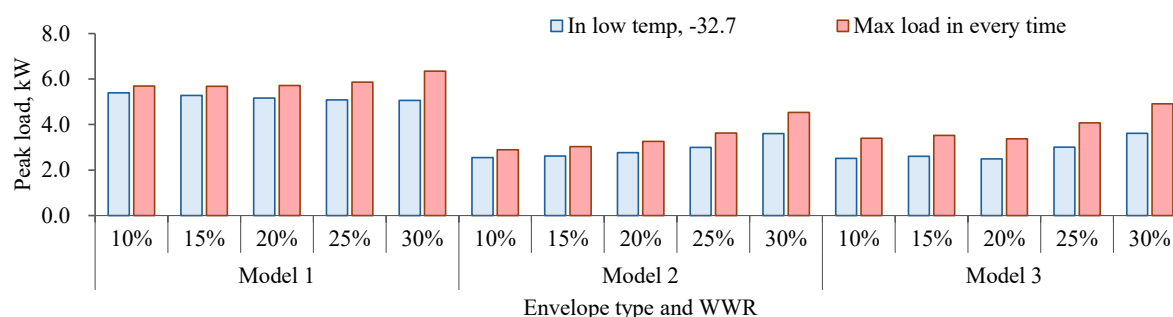


Figure 10. Peak heating load and heating load at $-32.7\text{ }^{\circ}\text{C}$ obtained from dynamic simulation.

The quantitative differences between these two values for each case are summarized in Table 5.

Table 5. Peak heating load and heating load at the minimum outdoor temperature ($-32.7\text{ }^{\circ}\text{C}$) from dynamic simulation for different envelope models and WWRs.

Model	WWR	Peak (kW)	$-32.7\text{ }^{\circ}\text{C}$ (kW)	Difference (%)
Model 1	10%	5.69	5.39	−5.27
	15%	5.69	5.28	−7.21
	20%	5.72	5.17	−9.62
	25%	5.86	5.08	−13.31
	30%	6.35	5.06	−20.31
Model 2	10%	2.89	2.54	−12.11
	15%	3.03	2.62	−13.53
	20%	3.26	2.76	−15.34
	25%	3.63	3.00	−17.36
	30%	4.53	3.60	−20.53
Model 3	10%	3.40	2.52	−25.88

15%	3.52	2.60	−26.14
20%	3.37	2.48	−26.41
25%	4.08	3.01	−26.23
30%	4.91	3.62	−26.27

The dynamic simulation results showed that the peak heating load did not necessarily occur at the minimum outdoor temperature. For Model 1, the heating load corresponding to $-32.7\text{ }^{\circ}\text{C}$ was 5–20% lower than the actual peak load, with the discrepancy increasing as the WWR increased. A similar trend was observed for Model 2, where the difference increased from approximately 12% at WWR = 10% to 21% at WWR = 30%. In contrast, Model 3 exhibited a consistently larger discrepancy of approximately 26% across all WWR conditions. Unlike Models 1 and 2, the discrepancy in Model 3 remained nearly constant across all WWR conditions, indicating that peak-load occurrence was influenced more strongly by factors other than WWR. This finding challenges the fundamental assumption of steady-state design practice that peak load occurs at the minimum outdoor temperature.

3.3. Seasonal Heating Energy Demand

The seasonal heating energy demand for all cases was calculated for the heating season (October 1–April 30), and the results obtained from the simplified methods were compared with those from the dynamic simulation. The comparison across the 15 cases is presented in Figure 11. The dynamic results show that seasonal heating demand decreases significantly as the WWR increases for all three models. In Model 1, the seasonal heating demand decreased from 14.97 MWh at WWR = 10% to 8.13 MWh at WWR = 30%. In Model 2, the seasonal heating demand decreased from 6.13 MWh to 3.59 MWh as the WWR increased from 10% to 30%. Similarly, in Model 3, the demand decreased from 6.09 MWh to 4.02 MWh. This indicates that solar gains and thermal storage play a dominant role in reducing heating demand under higher WWR conditions.

In contrast, Method 1 produced constant values irrespective of WWR, with annual heating demands of 21.13 MWh for Model 1 and 11.44 MWh for Models 2 and 3, which significantly overestimated the seasonal heating demand compared with the dynamic results. Depending on the model, under low WWR conditions (10–20%), the estimates were approximately 1.9–9.5 times higher, but the discrepancy increased with the WWR as dynamic demand decreased sharply.

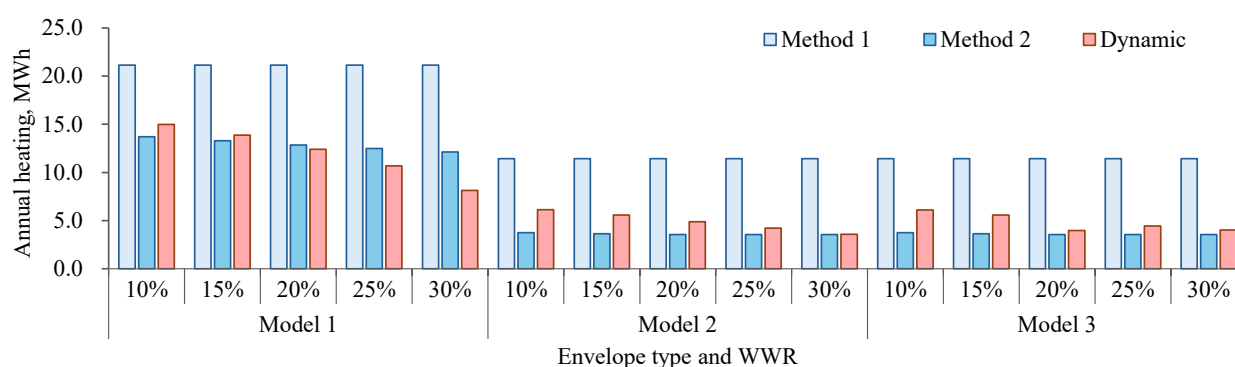


Figure 11. Comparison of seasonal heating demand obtained from Method 1, Method 2, and dynamic simulation.

Method 2 accounted for geometric characteristics and reproduced the overall decreasing trend of seasonal heating demand with increasing WWR. In Model 1, seasonal heating energy decreased from 13.70 MWh to 12.13 MWh as the WWR increased from 10%

to 30%. Similar reductions were observed in Models 2 and 3, where the predicted values decreased from 3.74 MWh to 3.54 MWh. However, the reduction predicted by Method 2 was considerably smaller than that obtained from the dynamic simulation. Although Method 2 reduced the error relative to Method 1 by partially accounting for solar heat gains, it did not account for the building's thermal mass. As a result, noticeable discrepancies remained between the simplified and dynamic results, particularly under conditions with larger window areas. This suggests that accounting for solar gains alone is insufficient to reproduce the combined effects of solar radiation and thermal mass.

Table 6 summarizes these differences using peak heating load, seasonal heating energy, and their relative errors. For seasonal heating energy in Model 1, Method 1 consistently overestimated the dynamic results, with relative errors ranging from 41.2% to 159.8%. Method 2 substantially reduced the error, with relative errors ranging from −8.4% to 49.1%. Unlike Models 2 and 3, Method 2 shifted from slight underestimation to overestimation as the WWR increased, suggesting that solar-gain effects were represented differently in the poorly insulated envelope. For Model 1, Method 2 slightly underestimated seasonal heating energy at WWR = 10–15%, with relative errors of −8.4% to −4.2%, but overestimated it at WWR = 20–30%, with relative errors ranging from 3.7% to 49.1%. For Model 2, Method 2 underestimated the dynamic results across all WWR values, although the error decreased from −39.0% at WWR = 10% to −1.5% at WWR = 30%. The decreasing underestimation with increasing WWR suggests that the representation of solar gains becomes increasingly effective as the window area increases. A similar trend was observed for Model 3, where the underestimation decreased from −38.6% to −11.8%. While Method 1 generally produced large overestimations that became more pronounced as the WWR increased, Method 2 provided closer agreement with the dynamic simulation results, although noticeable discrepancies remained depending on the envelope type and WWR.

Table 6. Peak heating load and seasonal heating energy with relative errors.

Model	WWR	Peak Heating Load (kW)			RE1 (%)	RE2 (%)	Seasonal Heating (MWh)			RE1 (%)	RE2 (%)
		Dyn	Method 1	Method 2			Dyn	Method 1	Method 2		
Model 1	10%	5.69	7.31	5.37	28.3	−5.7	14.97	21.13	13.70	41.2	−8.4
	15%	5.69	7.31	5.36	28.5	−5.8	13.87	21.13	13.29	52.4	−4.2
	20%	5.72	7.31	5.34	27.7	−6.6	12.39	21.13	12.84	70.6	3.7
	25%	5.86	7.31	5.33	24.7	−9.1	10.67	21.13	12.47	98.0	16.8
	30%	6.35	7.31	5.32	15.1	−16.3	8.13	21.13	12.13	159.8	49.1
Model 2	10%	2.89	3.95	1.68	36.8	−41.9	6.13	11.44	3.74	86.6	−39.0
	15%	3.03	3.95	1.72	30.6	−43.3	5.58	11.44	3.63	105.1	−34.9
	20%	3.26	3.95	1.76	21.3	−46.1	4.88	11.44	3.57	134.5	−26.8
	25%	3.63	3.95	1.80	9.0	−50.5	4.21	11.44	3.54	171.4	−15.9
	30%	4.53	3.95	1.83	−12.7	−59.5	3.59	11.44	3.54	218.1	−1.5
Model 3	10%	3.40	3.95	1.68	16.3	−50.6	6.09	11.44	3.74	87.7	−38.6
	15%	3.52	3.95	1.72	12.4	−51.2	5.58	11.44	3.63	105.0	−34.9
	20%	3.37	3.95	1.76	17.4	−47.8	3.97	11.44	3.57	187.9	−10.2
	25%	4.08	3.95	1.80	−3.1	−56.0	4.44	11.44	3.54	157.4	−20.2
	30%	4.91	3.95	1.83	−19.4	−62.6	4.02	11.44	3.54	184.8	−11.8

Note: Dyn—dynamic simulation; RE1, RE2—relative errors of Method 1 and Method 2.

Overall, Method 1 consistently overestimated seasonal heating demand across all models and WWR conditions, whereas Method 2 substantially reduced the error and reproduced the overall decreasing trend associated with increasing WWR. For the insulated Models 2 and 3, Method 2 showed relatively good agreement with the dynamic simulation at higher WWR values, although noticeable discrepancies remained. These results

suggest that seasonal heating energy demand is increasingly influenced by WWR and solar gains, whereas the influence of envelope-related thermal mass differences is less pronounced than in peak-load or hourly load analyses.

3.4. Load Duration Curve (LDC) Analysis

To further examine how heating demand is distributed over time and to compare differences between dynamic simulation and steady-state volumetric methods, load duration curves (LDCs), commonly used in district heating systems to represent peak and base-load demand and to inform system evaluation and equipment selection decisions, were constructed by ranking the heating load results in descending order (Figure 12).

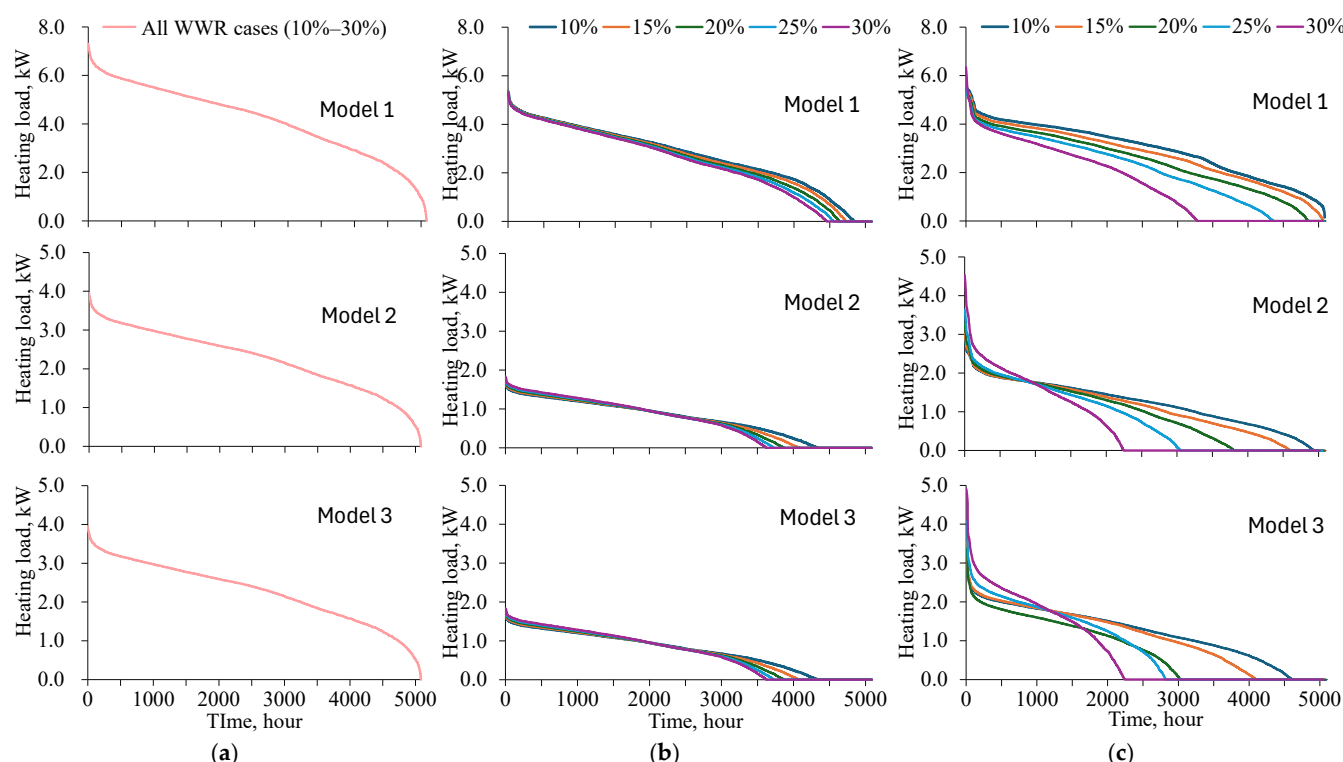


Figure 12. Load duration curves (LDC) of heating demand: (a) Method 1; (b) Method 2; (c) Dynamic simulation.

The results of Method 1 are presented in Figure 12a. Because the calculated values do not vary across WWRs of 10–30%, only one load duration curve is shown for each model. Method 1 consistently overestimates the heating load for all models. In contrast, the steady-state volumetric method with physically derived coefficients (Method 2) exhibits weaker sensitivity to window size and shows smaller differences between envelope types than those observed in the dynamic simulation (Figure 12b). The dynamic simulation results show that envelope effects vary across cases, with window size exerting a particularly strong influence (Figure 12c). Consequently, discrepancies between the curves, the steady-state methods, and the dynamic simulation become more pronounced during milder periods of the heating season, when the influence of outdoor temperature decreases and the relative contribution of solar gains increases, rather than during peak winter conditions.

The load duration curves help explain the differences in annual heating energy observed in the previous section. This relationship becomes more pronounced with increasing insulation level, suggesting that window area plays an increasingly important role in seasonal heating demand. Furthermore, although Models 2 and 3 show similar annual

heating-energy characteristics, Model 3 exhibits a more pronounced peak-load response, indicating that thermal mass has a greater influence on short-term heating load variations than on annual energy demand. The dynamic simulation revealed substantial variations in LDCs among the cases. In the insulated Models 2 and 3, larger WWR values substantially shortened the duration of non-zero heating demand, whereas the effect was less pronounced in Model 1. Method 1 showed no variation across WWR conditions, while Method 2 captured these differences only partially.

4. Discussion

4.1. Interpretation of Heating Load Behavior

Rather than being uniform, the accuracy of steady-state volumetric methods is strongly condition-dependent. This behavior can be explained by the increasing influence of solar gains as building insulation improves. As the window-to-wall ratio increases, solar radiation contributes more significantly to the building energy balance, but steady-state formulations primarily account for conductive heat losses and do not adequately represent solar gains, leading to systematic overestimation in normative steady-state approaches that neglect these effects. This may partly explain why the accuracy of the volumetric method varies across different WWR conditions [29].

Consistent with previous studies highlighting the importance of thermal mass in governing building thermal behavior [28–30], the present results indicate that its influence becomes increasingly important under conditions where conductive heat losses are reduced. This was particularly evident during transitional and low-load periods. These findings further suggest that thermal mass may affect the accuracy of volumetric heating load methods widely used in district heating practice, particularly in well-insulated buildings. In contrast, the influence of thermal-mass effects appears to be less pronounced in older, poorly insulated buildings, where conductive heat losses dominate the overall heating load behavior.

Furthermore, the mismatch between peak heating load and minimum outdoor temperature indicates that peak conditions are influenced by dynamic factors, highlighting a fundamental limitation of steady-state design assumptions. The observed differences of approximately 5–26% suggest that the common assumption of coincident peak load and minimum outdoor temperature may not always be valid, particularly in insulated buildings.

4.2. Implications for District Heating Applications

From a practical perspective, the applicability of steady-state methods should be interpreted as condition-dependent. They generally provide more reliable estimates under low solar influence and high heating demand, but their accuracy decreases as solar gains and thermal-mass effects become more significant. In addition, the use of normative tabulated values may introduce uncertainties associated with the selection of representative building categories and heat-loss coefficients, further affecting reliability.

In district heating practice, many buildings are typically involved, but detailed building-level data are often unavailable, particularly in cold-climate regions [13]. Under such conditions, the application of fully dynamic methods is often impractical. Therefore, simplified steady-state approaches remain necessary for preliminary load estimation and system planning, particularly during the early stages of district heating development.

These findings suggest that the key challenge is not to replace simplified methods with fully dynamic simulation but to improve their applicability and reliability under varying building conditions.

In this regard, the present results highlight the importance of considering the interaction between WWR, solar gains, and thermal mass. The effect of the WWR was not uniform. Although increasing WWRs generally reduced seasonal heating demand through higher solar gains, its influence on peak heating load was more pronounced, particularly in the lightweight building (Model 3). Compared with Model 2, Model 3 showed greater sensitivity to WWR, suggesting that thermal mass influences how peak heating loads respond to solar gains.

4.3. Applicability Framework

Based on these findings, the applicability of steady-state methods can be categorized according to building conditions. Under low solar influence (e.g., low WWR), steady-state methods are generally applicable. Under moderate solar influence (e.g., medium WWR), their use becomes conditional and may require correction. Under strong solar influence (e.g., high WWR) and low-load conditions, the accuracy of steady-state methods decreases substantially, and additional correction factors or improved simplified approaches may be required. These results suggest that WWR classification and thermal-mass effects should be considered when representing heating load variations in simplified volumetric methods.

The load duration curve (LDC) analysis provides additional system-level insight. In district heating systems, LDCs are used to distinguish peak- and base-load demands, supporting decisions on generation capacity, equipment sizing, and operational strategies [40]. Compared with dynamic simulation results, steady-state methods show weaker sensitivity to envelope characteristics, particularly window size, and discrepancies become more pronounced during milder periods of the heating season. This indicates that steady-state methods tend to overestimate base-load operation, potentially leading to excessive heat supply, indoor overheating, and reduced system efficiency.

4.4. Limitations

Several limitations of this study should be acknowledged. First, the dynamic simulation results were used as a reference for comparison; however, the THERB for HAM model results were not validated against measured building energy or indoor temperature data. Second, the analysis was conducted using a single representative weather dataset for Ulaanbaatar. Therefore, the results may differ when other standard weather datasets, actual meteorological years, or different climatic conditions are considered. In addition, several parameters related to solar-gain estimation were set to constant values based on previous studies, which may affect the applicability of the results under different solar-radiation conditions. Third, the analysis was based on three representative building models defined under simplified geometric and operational conditions. Consequently, the findings may not fully represent the diversity of building configurations encountered in district heating practice.

5. Conclusions

This study evaluated the accuracy and limitations of the steady-state volumetric method for calculating building heating loads under varying building envelope conditions. The results demonstrate that the accuracy of the method is not constant but follows a condition-dependent error structure governed by envelope type, insulation level, window-to-wall ratio (WWR), and thermal mass. As insulation performance improves, these factors exert a stronger influence, and the heating load behavior becomes increasingly time-dependent.

1. Method 1 and Method 2 showed substantially different performance. Method 1, which relies on normative coefficients and outdoor temperature, consistently overestimated heating demand across peak, monthly, seasonal, and LDC analyses. In contrast, Method 2 generally produced results closer to the dynamic simulation by incorporating envelope-specific heat-loss coefficients and solar gains. However, Method 2 consistently underestimated peak heating loads, with errors ranging from -62.6% to -5.7% . Because thermal-mass effects were not explicitly considered, noticeable differences from the dynamic reference results remained, particularly between Models 2 and 3, despite their similar U-values.
2. The influence of the WWR became increasingly pronounced as insulation performance improved. The largest discrepancies occurred during low-load periods, when solar gains and thermal-mass effects became more important. While Method 1 was unable to represent these effects, Method 2 improved the results by accounting for solar gains. However, the remaining discrepancies indicate that explicit representation of thermal-mass effects is required to further improve volumetric heating load methods.
3. U-value remained a dominant factor governing the overall magnitude of heating demand. However, despite having similar U-values, Models 2 and 3 exhibited different peak-load behavior, with Model 3 showing peak heating loads approximately 3–16% higher than Model 2. In contrast, seasonal heating demand was generally similar between the two models. These results suggest that thermal mass may influence peak-load behavior more strongly than seasonal heating demand and therefore may affect district heating peak-load estimation more significantly than annual energy estimation.
4. The largest discrepancies occurred in well-insulated buildings, particularly under high-WWR conditions and in the low-load portion of the LDC. These results indicate that future refinement of volumetric heating load methods should incorporate thermal-mass effects in addition to solar gains, particularly for highly insulated buildings with larger window areas. Although Method 2 improved the representation of heating-demand variation, it was unable to accurately reproduce peak-load behavior.
5. From a district heating perspective, the findings suggest that building classification should be extended beyond conventional indicators such as floor area, volume, and U-value to include envelope characteristics and WWR. Such information could support the development of improved simplified methods while maintaining the practicality required for district heating planning and operation.

Overall, the findings demonstrate that the accuracy of volumetric heating load methods is strongly influenced by insulation level, WWR, and thermal mass effects, and that these influences become increasingly important as building envelopes become more thermally efficient. The findings provide a basis for improving simplified district heating load estimation methods by incorporating envelope-related dynamic behavior while maintaining practical applicability. Future work will focus on developing an enhanced volumetric heating load method that explicitly incorporates solar-gain and thermal-mass effects, followed by validation across a wider range of representative building geometries and envelope configurations.

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Conflicts of 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.

Nomenclature and Abbreviations

The following nomenclature and abbreviations are used throughout this manuscript:

Nomenclature

Q_{bui}	Building heating load, W
q_{bui}	Specific heat-loss coefficient, $W \cdot m^{-3} \cdot K^{-1}$
q_{hg}	Specific heating load considering solar gains, $W \cdot m^{-3}$
q_{sol}	Solar heat gain per unit building volume, $W \cdot m^{-3}$
V_{bui}	Building volume, m^3
t_{in}	Indoor air temperature, $^{\circ}C$
t_{out}	Outdoor air temperature, $^{\circ}C$
ΔT	Indoor–outdoor temperature difference, K
U_{wall}	Thermal transmittance of wall, $W \cdot m^{-2} \cdot K^{-1}$
U_{wd}	Thermal transmittance of window, $W \cdot m^{-2} \cdot K^{-1}$
U_{ce}	Thermal transmittance of ceiling, $W \cdot m^{-2} \cdot K^{-1}$
U_i	Thermal transmittance of envelope component, $W \cdot m^{-2} \cdot K^{-1}$
I_s	Solar radiation intensity on south-facing wall, $W \cdot m^{-2}$
I_h	Horizontal solar radiation intensity, $W \cdot m^{-2}$
n_1	Solar orientation reduction factor, –
n_2	Window frame reduction factor, –
n_3	Dust reduction factor, –
c_p	Specific heat capacity, $J \cdot kg^{-1} \cdot K^{-1}$
Greek symbols	
α_{in}	Indoor surface heat transfer coefficient, $W \cdot m^{-2} \cdot K^{-1}$
α_{out}	Outdoor surface heat transfer coefficient, $W \cdot m^{-2} \cdot K^{-1}$
β	Indoor curtain effect factor, –
δ_i	Thickness of material layer, m
λ_i	Thermal conductivity of material layer, $W \cdot m^{-1} \cdot K^{-1}$
μ_{wd}	Window-to-wall ratio, –
ρ	Material density, $kg \cdot m^{-3}$

Abbreviations

DH	District Heating
DHS	District Heating System
BNbD	Building Norms and Regulations
THERB for HAM	Thermal Environment of a Residential Building for Heat, Air and Moisture Transfer
IWEC	International Weather for Energy Calculations
EPW	EnergyPlus Weather
WWR	Window-to-Wall Ratio
MAE	Mean Absolute Error
RE	Relative Error
R^2	Coefficient of Determination
LDC	Load Duration Curve

Appendix A. Thermophysical Properties of Envelope Materials

The detailed thermophysical properties of the envelope materials used in each building model are presented in Tables A1–A3.

Table A1. Thermophysical properties of envelope materials used in Model 1.

Envelope Component	Material	Thickness (m)	Thermal Conductivity (W·m ⁻¹ ·K ⁻¹)	Specific Heat Capacity, (J·kg ⁻¹ ·K ⁻¹)	Density, (kg·m ⁻³)
Wall	Cement mortar	0.020	1.91	917	2009
	Polystyrene concrete	0.350	0.55	1195	1600
Roof	Vapor barrier	0.005	0.038	1470	1800
	Expanded clay	0.250	0.091	840	400
	Glass wool	0.025	0.039	840	56
	Vapor barrier	0.0005	0.038	1470	1800
	Concrete	0.220	1.619	890	2206
	Cement Mortar	0.020	1.91	917	2009
Floor	Parquet	0.030	0.175	1880	408
	Glass wool	0.015	0.039	840	56
	Vapor barrier	0.0015	0.038	1470	1800
	Concrete	0.220	1.619	890	2206
Window	Glass	0.003	0.78	770	2540
	Air	0.016	0.022	1000	1.2
	Glass	0.003	0.78	770	2540

Table A2. Thermophysical properties of envelope materials used in Model 2.

Envelope Component	Material	Thickness (m)	Thermal Conductivity (W·m ⁻¹ ·K ⁻¹)	Specific Heat Capacity, (J·kg ⁻¹ ·K ⁻¹)	Density, (kg·m ⁻³)
Wall	Cement mortar	0.020	1.91	917	2009
	Polystyrene concrete	0.350	0.55	1195	1600
	Styrofoam	0.1	0.035	1470	21
	Cement mortar	0.020	1.91	917	2009
Roof	Vapor barrier	0.005	0.038	1470	1800
	Expanded clay	0.150	0.091	840	400
	Styrofoam	0.100	0.039	1470	21
	Vapor barrier	0.0005	0.038	1470	1800
	Concrete	0.220	1.619	890	2206
	Cement Mortar	0.020	1.91	917	2009
Floor	Parquet	0.030	0.175	1880	408
	Glass wool	0.015	0.039	0.039	840
	Vapor barrier	0.0015	0.038	0.038	1470
	Concrete	0.220	1.619	1.619	890
Window	Glass	0.003	0.78	770	2540
	Air	0.016	0.022	1000	1.2
	Glass	0.003	0.78	770	2540
	Air	0.016	0.022	1000	1.2
	Glass	0.003	0.78	770	2540

Table A3. Thermophysical properties of envelope materials used in Model 3.

Envelope Component	Material	Thickness (m)	Thermal Conductivity (W·m ⁻¹ ·K ⁻¹)	Specific Heat Capacity, (J·kg ⁻¹ ·K ⁻¹)	Density, (kg·m ⁻³)
Wall	Cement mortar	0.020	1.91	917	2009
	Fiber cement	0.012	0.187	840	1204
	Air layer	0.02	0.024	1000	1.2
	Vapor barrier	0.0015	0.038	1470	1800
	Plywood	0.012	0.103	1880	556
	Glass wool	0.14	0.048	840	56

	Styrofoam	0.04	0.035	1470	21
	Vapor barrier	0.0005	0.038	1470	1800
	Gypsum board	0.018	0.202	870	706
Roof	Iron	0.001	80.4	450	7900
	Vapor barrier	0.0005	0.038	1470	1800
	Plywood	0.012	0.103	1880	556
	Thin air layer	0.002	0.175	840	16
	Glass wool	0.21	0.048	840	56
	Vapor barrier	0.0005	0.038	1470	1800
	Gypsum board	0.009	0.202	870	706
Floor	Parquet	0.015	0.175	1880	408
	Vapor barrier	0.0015	0.039	1470	1800
	Concrete	0.100	1.619	890	2206
	Vapor barrier	0.0015	0.038	1470	1800
	Styrofoam	0.1	0.035	1470	21
	Vapor barrier	0.0015	0.038	1470	1800
	Concrete	0.100	1.619	890	2206
Window	Glass	0.003	0.78	770	2540
	Air	0.016	0.022	1000	1.2
	Glass	0.003	0.78	770	2540
	Air	0.016	0.022	1000	1.2
	Glass	0.003	0.78	770	2540

Appendix B. Normative Specific Heat-Loss Coefficients

The normative values used for selecting the specific heat-loss coefficients are summarized in Tables A4 and A5.

Table A4. Specific heat loss of an old concrete building, $W \cdot m^{-3} \cdot K^{-1}$ [35].

№	Building Volume, m ³	Built Before 1958	Built Since 1958
1	~100	0.86	1.07
2	~200	0.77	0.95
3	~300	0.72	0.91
4	...	...	...
5	~50,000	0.31	0.40

Table A5. Specific heat loss of low-rise housing, $W \cdot m^{-3} \cdot K^{-1}$ [19].

№	Building Area, m ²	Building Floor			
		1	2	3	4
1	~50	0.579	NA	NA	NA
2	~100	0.517	0.558	NA	NA
3	~150	0.455	0.496	0.538	NA
4	~250	0.414	0.434	0.455	0.476
5	~400	0.372	0.372	0.393	0.414
6	~600	0.359	0.359	0.359	0.372
7	More than 1000	0.336	0.336	0.336	0.336

References

1. Lund, H.; Möller, B.; Mathiesen, B.V.; Dyrelund, A. The role of district heating in future renewable energy systems. *Energy* **2010**, *35*, 1381–1390. <https://doi.org/10.1016/j.energy.2009.11.023>.
2. Lund, H.; Østergaard, P.A.; Chang, M.; Werner, S.; Svendsen, S.; Sorknæs, P.; Thorsen, J.E.; Hvelplund, F.; Mortensen, B.O.G.; Mathiesen, B.V.; et al. The status of 4th generation district heating: Research and results. *Energy* **2018**, *164*, 147–159. <https://doi.org/10.1016/j.energy.2018.08.206>.
3. Sayegh, M.A.; Danielewicz, J.; Nannou, T.; Miniewicz, M.; Jadwiszczak, P.; Piekarska, K.; Jouhara, H. Trends of European research and development in district heating technologies. *Renew. Sustain. Energy Rev.* **2017**, *68*, 1183–1192. <https://doi.org/10.1016/j.rser.2016.02.023>.
4. Kristensen, M.H.; Hedegaard, R.E.; Petersen, S. Long-term forecasting of hourly district heating loads in urban areas using hierarchical archetype modeling. *Energy* **2020**, *201*, 117687. <https://doi.org/10.1016/j.energy.2020.117687>.
5. Li, X.; Li, W.; Zhang, R.; Jiang, T.; Chen, H.; Li, G. Collaborative scheduling and flexibility assessment of integrated electricity and district heating systems utilizing thermal inertia. *Appl. Energy* **2020**, *258*, 114021. <https://doi.org/10.1016/j.apenergy.2019.114021>.
6. Chen, G.; Lu, S.; Zhou, S.; Tian, Z.; Kim, M.K.; Liu, J.; Liu, X. A Systematic Review of Building Energy Consumption Prediction: From Perspectives of Load Classification, Data-Driven Frameworks, and Future Directions. *Appl. Sci.* **2025**, *15*, 3086. <https://doi.org/10.3390/app15063086>.
7. Billanes, J.D.; Ma, Z.G.; Jørgensen, B.N. Data-Driven Technologies for Energy Optimization in Smart Buildings: A Scoping Review. *Energies* **2025**, *18*, 290. <https://doi.org/10.3390/en18020290>.
8. Hua, P.; Wang, H.; Xie, Z.; Lahdelma, R. District heating load patterns and short-term forecasting. *Energy* **2024**, *289*, 129866. <https://doi.org/10.1016/j.energy.2023.129866>.
9. Sun, Y.; Haghighat, F.; Fung, B.C.M. A review of data-driven approaches for building energy prediction. *Energy Build.* **2020**, *221*, 110022. <https://doi.org/10.1016/j.enbuild.2020.110022>.
10. Magni, M.; Ochs, F.; De Vries, S.; Maccarini, A.; Sigg, F. Detailed comparison of building energy simulation tools. *Energy Build.* **2021**, *250*, 111260. <https://doi.org/10.1016/j.enbuild.2021.111260>.
11. Moreau, V.; Laurent, M.-H.; Berthou, T.; Duplessis, B.; Stabat, P. High-Resolution Building Stock Energy Model for Assessing the Impact on the Load Curve of Residential Space Heating Electrification. *Energy Build.* **2025**, *345*, 116069. <https://doi.org/10.1016/j.enbuild.2025.116069>.
12. Goy, S.; Maréchal, F.; Finn, D. Data for Urban Scale Building Energy Modelling: Assessing Impacts and Overcoming Availability Challenges. *Energies* **2020**, *13*, 4244. <https://doi.org/10.3390/en13164244>.
13. Masson, V.; Heldens, W.; Bocher, E.; Bonhomme, M.; Bucher, B.; Burmeister, C.; de Munck, C.; Esch, T.; Hidalgo, J.; Kanani-Sühring, F.; et al. City-Descriptive Input Data for Urban Climate Models: Model Requirements, Data Sources and Challenges. *Urban Clim.* **2020**, *31*, 100536. <https://doi.org/10.1016/j.uclim.2019.100536>.
14. EN 12831-1:2017; Energy Performance of Buildings—Method for Calculation of the Design Heat Load. European Committee for Standardization: Brussels, Belgium, 2017.
15. DIN/TS 12831-1:2020-04; Energy Performance of Buildings—Method for Calculation of the Design Heat Load—National Supplement. DIN Beuth Verlag: Berlin, Germany, 2020.
16. GB 50736–2012; Design Code for Heating, Ventilation and Air Conditioning of Civil Buildings. Ministry of Housing and Urban-Rural Development of the People’s Republic of China: Beijing, China, 2012.
17. Hao, Z.; Xie, J.; Zhang, X.; Liu, J. Simplified model of heat load prediction. *Buildings* **2023**, *13*, 1076. <https://doi.org/10.3390/buildings13041076>.
18. Lee, H.J.; Ryu, S.W. Analysis of unit heating loads for non-residential buildings. *KIEAE J.* **2022**, *22*, 5–14. <https://doi.org/10.12813/kieae.2022.22.6.005>.
19. BNbD 41-02-13; District Heating. Ministry of Urban Development, Construction and Housing: Ulaanbaatar, Mongolia, 2014.
20. SNiP 41-02-2003; Heating Networks. Gosstroy of Russia: Moscow, Russia, 2003.
21. Sokolov, E.Y. *District Heating and Heating Networks: Textbook for Universities*, 7th ed.; Izdatelstvo MEI: Moscow, Russia, 2001.
22. Melekhin, A.A. Development of an Engineering Calculator for the Technical and Economic Calculation of Thermal Protection of Buildings. *IOP Conf. Ser. Mater. Sci. Eng.* **2021**, *1079*, 042046.

23. Gavrylenko, M.; Fedirko, M.; Dziubanovska, N.; Pyrih, H.; Brych, V.; Halysh, N. Modeling of the Temperature Regime of the District Heating System in the Context of Energy Efficiency and Reduction of Environmental Impact. In Proceedings of the 2020 IEEE International Conference on Problems of Infocommunications, Science and Technology (PIC S&T), Kharkiv, Ukraine, 6–9 October 2020; pp. 136–139.
24. Melikyan, Z. Residential buildings: Heating loads. In *Encyclopedia of Energy Engineering and Technology*; Capehart, B., Ed.; CRC Press: Boca Raton, FL, USA, 2007; pp. 1272–1277. <https://doi.org/10.1201/9780849338960.ch148>.
25. Fouda, A.; Melikyan, Z.; Mohamed, M.A.; Elattar, H.F. A modified method of calculating heating load. *Energy Build.* **2014**, *75*, 170–175. <https://doi.org/10.1016/j.enbuild.2014.01.047>.
26. Huynh, A.; Dias Barkokebas, R.; Al-Hussein, M.; Cruz-Nogues, C.; Chen, Y. Energy-Efficiency Requirements for Residential Building Envelopes in Cold-Climate Regions. *Atmosphere* **2021**, *12*, 405. <https://doi.org/10.3390/atmos12030405>.
27. *BNbD 25-01-2020; Building Insulation*. Ministry of Urban Development, Construction and Housing: Ulaanbaatar, Mongolia, 2020.
28. Shafigh, P.; Asadi, I.; Mahyuddin, N.B. Concrete as a Thermal Mass Material for Building Applications: A Review. *J. Build. Eng.* **2018**, *19*, 14–25. <https://doi.org/10.1016/j.jobbe.2018.04.021>.
29. Cheng, R.; Zhang, N.; Zhang, W.; Sun, Y.; Yin, B.; Gao, W. Impact of Thermal Mass, Window Performance, and Window-to-Wall Ratio on Indoor Thermal Dynamics in Public Buildings. *Buildings* **2025**, *15*, 1757. <https://doi.org/10.3390/buildings15101757>.
30. Reilly, A.; Kinnane, O. The Impact of Thermal Mass on Building Energy Consumption. *Appl. Energy* **2017**, *198*, 108–121. <https://doi.org/10.1016/j.apenergy.2017.04.024>.
31. Chi, F.; Wang, Y.; Wang, R.; Li, G.; Peng, C. Optimal window-to-wall ratio analysis. *Sol. Energy* **2020**, *195*, 64–81. <https://doi.org/10.1016/j.solener.2019.11.033>.
32. *SNiP II-3-79; Thermal Engineering Design of Civil Buildings*. Gosstroy of the USSR: Moscow, Russia, 1979.
33. Attia, S.; Gratia, E.; De Herde, A.; Hensen, J.L.M. Simulation-based decision support tool. *Energy Build.* **2012**, *49*, 2–15. <https://doi.org/10.1016/j.enbuild.2012.01.028>.
34. Marino, C.; Nucara, A.; Pietrafesa, M. Effect of window-to-wall ratio on energy consumption. *J. Build. Eng.* **2017**, *13*, 169–183. <https://doi.org/10.1016/j.jobbe.2017.08.001>.
35. Ministry of Energy and Housing and Communal Services of Sverdlovsk Oblast. *Methodical Guidelines for Filling Out an Energy Passport of a Budgetary Institution*. Yekaterinburg, Russia, 2009.
36. Bogoslovsky, V.N.; Krupnov, B.A.; Skanavi, A.N.; Egiazarov, A.G.; Mikhailov, L.M.; Nevskii, V.V.; Moor, L.F.; Shilkrot, E.O.; Naumov, A.L.; Finkelshtein, S.M.; et al. *Designer's Handbook: Internal Sanitary-Technical Installations. Part I: Heating*, 4th ed.; Stroyizdat: Moscow, Russia, 1990.
37. Ozaki, A.; Watanabe, T.; Takase, S. Simulation Software of the Hygrothermal Environment of Buildings Based on Detailed Thermodynamic Models. In Proceedings of the 3rd IBPSA Conference (Building Simulation 2003), Eindhoven, The Netherlands, 11–14 August 2003; pp. 45–54.
38. Ozaki, A.; Tsujimaru, T. Prediction of Hygrothermal Environment of Buildings Based upon Combined Simulation of Heat and Moisture Transfer and Airflow. In Proceedings of the 9th IBPSA Conference (Building Simulation 2005), Montréal, Canada, 2005; pp. 899–906.
39. Repository of Building Simulation Climate Data from the Creators of the EPW. Available online: <https://climate.onebuilding.org> (accessed on 1 June 2026).
40. Nussbaumer, T.; Thalmann, S.; Jenni, A.; Ködel, J. *Handbook on Planning of District Heating Networks*; Swiss Federal Office of Energy: Bern, Switzerland, 2020.

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