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Article

AI-Guided Evolutionary Optimization of Passive Solar Design for Residential Heating Across Distinct Climate Zones

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Abstract

Achieving meaningful reductions in residential heating demand requires design strategies that can respond to climate-specific solar availability and envelope performance. Although passive solar principles are well established, their effectiveness remains highly context-dependent, and simplified prescriptive approaches may not capture interactions across different climates. This study presents an AI-guided evolutionary optimization framework for passive solar residential design, focusing exclusively on the reduction in annual space heating demand under standardized assumptions. A standardized single-story residential prototype is simulated across three climatic contexts: hot-dry (Riyadh), temperate (Barcelona), and cold (Toronto). Dynamic building performance simulations are conducted using EnergyPlus, coupled with DesignBuilder's built-in NSGA-II evolutionary optimization engine. Envelope-related variables, including the window-to-wall ratio, orientation, glazing configuration, and thermal mass, are optimized using a single objective: minimizing the annual heating load under idealized heating conditions. The results demonstrate substantial climate-dependent reductions in heating demand. In Toronto, the annual heating demand is reduced from approximately 16,900 kWh to 9600 kWh (~43%). In Barcelona, a reduction from approximately 5650 kWh to 1990 kWh (~65%) is achieved, while in Riyadh, heating demand is reduced from approximately 990 kWh to 39 kWh (>95%). The optimized solutions reveal distinct climate-specific design logic rather than universal passive rules. The results demonstrate that evolutionary optimization can support early-stage envelope design by revealing climate-specific heating strategies under clearly defined and comparable assumptions.

Keywords: passive solar design; residential heating demand; AI-guided optimization; building energy simulation; climate-responsive architecture

1. Introduction

Residential buildings remain a primary consumer of global energy. In both temperate and cold climates, space heating constitutes a dominant load, while in many hot regions, space heating is a seasonal but still important requirement [1–3]. Even though decarbonization strategies often prioritize active systems and renewable supply, the building envelope and the configuration of passive solar elements continue to shape heating demand through clearly identifiable mechanisms [4]. Specifically, they govern transmission heat-loss pathways, determine the availability of useful solar gains, and influence the timing and magnitude of indoor heat deficits. Decisions made in early design stages, such as decisions on orientation, window ratio, glazing choice, and the incorporation of thermal mass, are therefore crucial for residential prototypes, as they can establish heating demand characteristics that tend to persist over the service life of a dwelling [5–7]. This dependence encourages strategies that focus on strong passive solutions during the design phase rather than relying on corrective measures later.

A persistent methodological challenge arises from the nonlinear interaction of passive design variables. For example, increasing the window-to-wall ratio may improve winter solar gains in heating-dominated climates, but it can also increase transmission losses if the glazing performance is insufficient or if the orientation does not align with seasonal solar paths [7]. Thermal mass offers another example of a methodological challenge. While it can dampen temperature swings and improve heat retention, its effectiveness depends on solar availability, internal gains, and the timing of heat delivery [8]. These complex relationships imply much broader design options than those that can be explored by manual testing, especially when focusing only on heating demand and considering multiple climates within one analysis.

In response, simulation-based optimization has become increasingly common. Evolutionary methods, including genetic algorithms, are frequently applied to navigate high-dimensional design spaces and to identify high-performing configurations under constraints [7,9]. At the same time, surrogate modeling and machine learning approaches have been introduced to reduce computational cost and to support broader exploration, including early-stage analysis under uncertainty [10,11]. These methodological developments are especially relevant to passive solar design, where solution landscapes often contain multiple local optima and strong variable coupling [4,12]. Optimization tools can reveal viable combinations that would otherwise remain untested.

Despite this progress, there are two limitations of recent work that have motivated the present study. First, many optimization studies frame heating performance as one element within a multi-objective formulation that also includes cooling, cost, comfort indices, or carbon metrics [13,14]. Such approaches are valuable, yet they can obscure the specific contribution of solar-responsive passive decisions to reductions in heating load. Improvements may instead be driven by changes in HVAC efficiency, operational control, or objective weighting rather than by envelope behavior itself. Second, cross-climatic comparisons are often difficult to interpret. In studies, building forms, internal gains, occupancy assumptions, or system definitions are frequently modified under different climates, which limits causal inference regarding how passive optimization logic depends on climate alone [1,2].

This study addresses these limitations through a deliberately bounded research question: to what extent can annual residential heating demand be reduced through AI-guided optimization of passive and solar-responsive design variables when conditions related to building geometry and comfort are constant and cooling is excluded? The analysis is structured around a standardized residential prototype simulated across three climatic contexts that represent hot and dry, temperate, and cold and humid conditions. The optimization objective is defined as the minimization of annual heating load, expressed in kilowatt-hours, using an ideal-load representation [15]. This formulation isolates envelope-driven demand rather than system efficiency effects. Heating load serves as a direct and interpretable indicator of passive performance in early-stage design assessments because it reflects the combined outcome of transmission losses, infiltration, and useful solar gains.

A further motivation concerns the gap between simulation-based expectations of passive solar performance and the outcomes observed in practice. Conceptual evidence suggests that discrepancies often emerge when design assumptions diverge from operational realities [4]. While post-occupancy validation lies outside the scope of the present work, this study addresses a related concern by making all modeling and optimization assumptions explicit and consistent across climates. This transparency enables the results to be interpreted as conditional on clearly stated boundaries. It also supports replication and serves as a basis for extensions that include uncertain occupancy, adaptive comfort models, or calibrated data.

This study makes two main contributions. First, it offers a controlled cross-climate comparison of AI-guided passive optimization outcomes using a consistent residential prototype and a single heating-focused objective. Second, it interprets the resulting design patterns as climate-specific optimization logic, identifying which classes of variables dominate in each context and why, in physical terms.

The remaining sections of the paper are organized as follows: Section 2 reviews recent work on AI-assisted passive optimization and solar-responsive envelope design, positioning the present study relative to existing approaches and identified gaps. Section 3 describes the simulation model, climatic datasets, optimization formulation, and reproducibility provisions. Section 4 reports baseline and optimized results for Riyadh, Barcelona, and Toronto, followed by a cross-climate comparison. Section 5 discusses climate-dependent optimization logic and its implications for early-stage residential design. Section 6 concludes with a succinct statement of this study's contributions and limitations and outlines directions for further research.

2. Background and Related Work

In this section, prior work on passive and solar-responsive design, AI-based optimization in building energy research, and approaches that focus specifically on heating demand across climates is reviewed. The review is structured to identify methodological trends and recurring limitations that motivate the present study.

2.1. Passive and Solar-Responsive Designs as Variables of Heating Demand

Passive design strategies have long been recognized as key determinants of residential heating demand. Their influence operates primarily through transmission losses, infiltration behavior, and the availability of useful solar gains [1,8]. Envelope configuration, glazing performance, building orientation, and the presence of thermal mass together shape the balance between heat loss and heat acquisition during the heating season [4,5]. In low-rise residential typologies, particularly in cold and temperate climates, these factors often exert a stronger influence on heating demand than system efficiency because surface area-to-volume ratios are relatively high [3].

Recent comparative studies confirm that decisions related to solar-responsive envelope design can significantly reduce heating demand when they are aligned with local climatic conditions [6,7]. Examples include orienting glazing to the south, optimizing window-to-wall ratios, and using high-performance glazing systems. The literature also stresses that these strategies only work in certain situations. Increasing the amount of glass may help winter solar gains, but it can also be counterproductive if the losses from transmission are greater than the gains or if the orientation does not match the seasonal solar paths [7]. This conditional behavior complicates rule-based passive design approaches and motivates the use of computational exploration.

Thermal mass exhibits a similar climate-sensitive role. In cold climates, heavyweight constructions can lead to improved heat retention and dampened indoor temperature fluctuations, which reduces heating peaks and annual demand [2,8]. In hot and dry climates, thermal mass is more frequently discussed in relation to cooling performance. Its contribution to winter heating remains less explored, despite the fact that heating demand is not negligible [9]. Taken together, the literature indicates that passive heating optimization cannot be performed by relying on isolated parameter adjustments. Instead, it requires consideration of interactions among multiple envelope-related variables [16,17].

2.2. Evolutionary and AI-Based Optimization in Building Energy Design

To address the nonlinear and high-dimensional nature of passive design problems, evolutionary optimization methods have been widely adopted in building energy research. Genetic algorithms and related evolutionary techniques are particularly well suited to this context because they do not rely on gradient information and can explore complex design spaces characterized by strong variable coupling and multiple local optima [9,11]. Recent systematic reviews confirm the continued expansion of AI-driven multi-objective optimization in building energy retrofit and design decision support, highlighting the integration of evolutionary search with energy, cost, and resilience objectives [18].

Within building performance applications, evolutionary algorithms are commonly integrated with dynamic simulation engines to evaluate large numbers of design alternatives under physically consistent conditions. Recent studies demonstrate that GA- and NSGA-II-based optimization frameworks remain actively used for envelope design, early-stage decision support, and energy-demand reduction across different climatic contexts, particularly where multiple design variables interact in nonlinear ways [19,20]. These approaches are often described as AI-assisted because they employ intelligent search and selection mechanisms to guide exploration of the design space, even though they do not rely on predictive learning or data-driven inference.

More recent AI-based optimization research has also expanded toward hybrid frameworks that combine evolutionary searches with surrogate modeling or machine learning approximations in order to reduce computational cost [10]. While such approaches can enable broader exploration, they introduce additional modeling layers and assumptions that may obscure the direct relationship between design variables and physical performance outcomes. As a result, several authors continue to emphasize the value of direct evolutionary optimization coupled with full dynamic simulation when interpretability and methodological transparency are priorities, particularly in early-stage building design [19]. Recent multidimensional AI-assisted optimization studies further demonstrate the integration of evolutionary search with advanced control and predictive modeling techniques to enhance thermal and energy performance [21]. Despite their methodological maturity, many evolutionary optimization studies adopt multi-objective formulations that combine heating, cooling, cost, emissions, and comfort metrics within a single problem [13,14]. While these formulations are valuable for holistic assessment, they can complicate interpretation by making it difficult to isolate the specific contribution of envelope-level and solar-responsive design variables to heating demand reductions. In such cases, improvements in heating performance may arise indirectly from system efficiency, control strategies, or objective weighting rather than from passive design behavior itself.

Taken these findings together, the recent literature confirms that evolutionary optimization remains a current and methodologically robust AI-based approach to performing energy analysis. However, it also highlights the importance of clearly defining optimization objectives and analytical boundaries when the research aim is to understand climate-dependent passive design logic rather than to pursue generalized multi-criteria optimality.

2.3. Optimization Focused on Heating and the Role of Objective Definition

Recent studies have increasingly addressed heating demand as a primary or dominant optimization objective. Studies conducted in cold climates show that optimizations aimed at reducing heating demand tend to prioritize high-performance glazing, reduced infiltration, and increased thermal mass. Solar gains play a complementary role that depends on orientation and shading control [3,22]. These findings suggest that heating demand follows a different hierarchy of governing variables than cooling demand, even when both occur within the same building. Multi-climatic envelope optimization studies further confirm that design-variable sensitivity varies significantly across climate zones, even under comparable objective formulations [23].

However, most research centered on heating is specific to a certain climate. Few studies adopt a unified framework that enables direct cross-climatic comparison. When multiple climates are considered, changes in building form, occupancy assumptions, or HVAC representations often accompany climate variations. Such changes limit causal inference regarding whether differences in optimized solutions arise from climatic drivers or from modeling inconsistencies [1,2].

Another methodological issue concerns the representation of HVAC systems. A number of studies include detailed heating system models, which can make it hard to observe effects at the envelope level. In such cases, reductions in heating demand may be conflated with system efficiency improvements or control logic adjustments. In response, some authors advocate for the use of ideal-load- or demand-based representations for evaluating passive performance rather than system design [15,24]. This approach allows for clearer attribution of results to envelope- and solar-responsive variables.

2.4. Cross-Climatic Comparisons and the Adaptability of Optimization Logic

Cross-climatic studies provide insight into the transferability of passive design strategies. Comparative research indicates that optimized envelope variables do not scale uniformly with climatic severity. Window areas that perform well in temperate climates may prove excessive in cold climates unless they are paired with advanced glazing and carefully selected orientations [7,22]. Similarly, strategies that are effective in hot and dry regions during winter can differ fundamentally from those applied in temperate zones, even when solar availability appears comparable [9].

AI-based optimization provides a means to uncover how designs perform in different climates by obtaining solutions from performance-driven searches rather than prescriptive assumptions. Nevertheless, the literature shows that relatively few studies have analyzed why optimized solutions diverge across climates in physical terms. Aspects such as the relative contribution of solar gains, the dominance of transmission losses, or the stabilizing role of thermal mass are often only implied [4]. Without such interpretation, optimization results risk being treated as black-box outputs rather than as sources of transferable design knowledge.

Recent analyses further highlight the gap between simulation-based passive solar predictions and realized building performance. These research investigations emphasize the value of transparent assumptions and cautious framing of conclusions [4]. Although this does not mean that optimization-based research is invalid, it reinforces the importance of clearly bounded claims and reproducible modeling choices [25].

2.5. Identified Research Gap and Positioning of the Present Study

The reviewed body of related work contains three inter-related gaps:

- Studies that focus only on heating optimization that isolate passive and solar-responsive effects without conflating them with cooling performance or HVAC efficiency remain limited;
- Cross-climatic comparisons are often undermined by inconsistent modeling assumptions, which restrict the ability to attribute differences in optimized solutions to climate alone;
- While AI-guided optimization is widely applied, fewer studies translate optimization outcomes into interpretable, climate-specific design logic that is relevant to early-stage residential design.

By applying a consistent AI-guided optimization framework to a standardized residential prototype across three distinct climate zones, the present study addresses these gaps. A single objective focused on annual heating load is used throughout. The analysis enables direct comparison of optimization outcomes and supports interpretation of climate-driven design tendencies by maintaining constant geometry, comfort parameters, and HVAC representation. By prioritizing passive and solar-responsive strategies across different climatic contexts, this study provides both quantitative results and structured insight.

3. Methodologies

This section describes the framework and methodology used to evaluate the impact of passive and solar-responsive design strategies on residential space heating demand. The approach combines dynamic building energy simulations with AI-guided evolutionary optimization under a deliberately constrained set of assumptions. The methodology prioritizes transparency and cross-climatic comparability, ensuring that differences in performance outcomes arise from climate-driven design responses rather than changes in geometry, comfort criteria, or HVAC representation. The following subsections describe the research design, case study selection, model definition, optimization formulation, and analytical boundaries.

3.1. Overall Research Design

This study employs a simulation-based AI-guided evolutionary optimization framework to evaluate the potential of passive and solar-responsive design strategies to reduce space heating demand in residential buildings across distinct climate zones. The methodological framework is

intentionally constrained in order to isolate envelope-driven effects and enable cross-climatic comparison under consistent assumptions.

The research methodology follows a sequential structure. It begins with the definition of a standardized residential prototype, followed by climate-specific baseline simulation. AI-guided parametric optimization is then performed using a single objective focused on heating demand. The final stage consists of comparative analysis and interpretation of optimized solutions across the selected climates. Throughout all stages, building geometry, occupancy assumptions, comfort setpoints, and HVAC representation are constant. Climate is treated as the sole external differentiating variable.

3.2. Case Study Locations and Climate Data

Three cities were selected to represent distinct residential heating contexts spanning a broad climatic gradient. Riyadh (Saudi Arabia) represents a hot desert climate characterized by high annual solar radiation and limited winter heating demand, while Barcelona (Spain) reflects a temperate Mediterranean climate with moderate seasonal heating requirements and Toronto (Canada) represents a cold and humid continental climate with prolonged and energy-intensive winter conditions. The climatic classifications and heating-relevant indicators for the selected cities are summarized in Table 1.

Climatic classification is reported using both the Köppen and ASHRAE climate zoning systems to ensure international comparability. In addition to categorical classifications, heating-relevant quantitative indicators are provided, including heating degree days (HDD18), annual mean air temperature, and global horizontal irradiance (GHI). HDD18 serves as an indicator of climatic heating severity, while GHI reflects the availability of passive solar gains. Together, these metrics form the boundary conditions under which the heating-focused optimization was conducted.

Table 1. Climatic characteristics and heating-relevant indicators of selected case study locations based on IWECEPW weather files.

City	Country	Köppen Climate	ASHRAE Zone	HDD18 (°C·Days)	Annual Mean Temp. (°C)	Annual GHI (kWh/m²)	EPW Source
Riyadh	Saudi Arabia	BWh—Hot desert	1B	450	26.5	2200	IWECEPW
Barcelona	Spain	Csa—Mediterranean	3C	1400	18.2	1650	IWECEPW
Toronto	Canada	Dfa—Cold humid	6A	3400	9.4	1400	IWECEPW

¹ Values are derived from IWECEPW datasets and rounded to the nearest 50 degree-days.

Hourly EnergyPlus Weather (EPW) files were used for all simulations [23]. Each model was simulated over a full annual period from 1 January to 31 December in order to capture seasonal heating dynamics.

3.3. Residential Prototype Definition

A standardized single-story residential prototype was defined to represent a common low-rise housing typology while minimizing geometric complexity. The building has a square plan measuring 10 m × 10 m, corresponding to a gross floor area of 100 m² and a conditioned floor area of 94.2 m². The story height is 3.0 m, resulting in a conditioned volume of 282.6 m³.

To maintain methodological consistency across all optimization runs, the dwelling was modeled as a single thermal zone. This simplification avoids intra-zonal variability and ensures that performance differences arise exclusively from variations in envelope configuration and solar-responsive parameters rather than internal zoning effects. The prototype geometry and spatial configuration are illustrated in Figure 1.

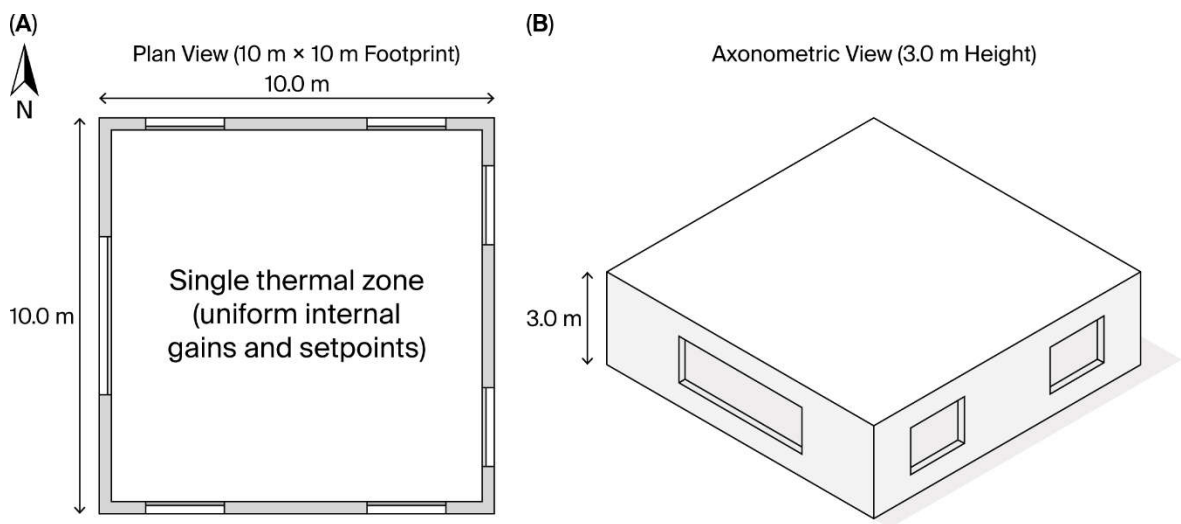


Figure 1. Standardized residential prototype used for AI-guided evolutionary optimization: (A) plan view, showing 10 m × 10 m footprint and single-thermal-zone configuration; (B) axonometric view, illustrating 3.0 m story height and distributed façade openings. Window-to-wall ratio (20%–80%) and envelope properties were treated as optimization variables, while geometry remained fixed across all climate cases.

3.4. Envelope Construction and Airtightness Assumptions

Baseline envelope constructions were defined to represent energy-code-compliant residential assemblies commonly used in contemporary low-rise housing. The objective was not to reproduce region-specific construction traditions, but to establish a consistent and realistic reference condition against which the effects of passive and solar-responsive optimization could be evaluated across different climates.

The external wall assembly corresponds to a lightweight, code-compliant construction with a thermal transmittance (U-value) of 0.354 W/m²·K. The roof is modeled as a lightweight flat roof with a U-value of 0.346 W/m²·K, while the ground floor is represented by a lightweight slab-on-grade construction with a U-value of 0.314 W/m²·K. These envelope properties were applied uniformly across all climate cases to ensure that observed performance differences arise from climatic drivers and optimized design variables rather than baseline construction inconsistencies.

Airtightness was represented using a constant infiltration rate of 0.7 air changes per hour, applied continuously throughout the year and across all simulations. By fixing infiltration assumptions, the influences of envelope configuration and solar-responsive parameters on heating demand are isolated, avoiding confounding effects associated with variable air leakage behavior. This approach supports controlled cross-climatic comparison and aligns with the study’s focus on envelope-driven heating performance rather than operational variability.

3.5. Glazing and Window Configuration (Baseline)

The baseline glazing configuration was defined to represent a conservative residential condition with limited intentional exploitation of solar gains. Clear single glazing with a nominal thickness of 6 mm was used throughout the dwelling. The window-to-wall ratio was set to 20%, with windows distributed uniformly across all façades.

No external shading devices or internal blinds were included in the baseline model. This configuration establishes a neutral reference condition in which solar access is neither maximized nor deliberately restricted. As such, it provides a clear baseline against which the effects of optimized glazing performance, window area, orientation, and shading strategies can be evaluated.

Window dimensions and placement were kept constant in the baseline model and only modified within the bounds defined by the optimization variables. This approach ensures that the changes in

heating demand observed in the optimized solutions can be attributed to controlled design decisions rather than inconsistencies in baseline fenestration definitions.

3.6. HVAC Representation and Comfort Conditions

To isolate heating demand that is solely attributable to the building envelope and passive design decisions, an ideal-load, heating-only HVAC representation was employed in this study. In this approach, the thermal energy required to maintain indoor comfort is calculated without modeling system efficiency, distribution losses, or control strategies. By decoupling heating demand from HVAC system performance, envelope heat transfer, infiltration losses, and useful solar gains are explicitly focused on.

Heating operation was enabled throughout the simulations, while cooling systems were intentionally disabled in all cases to maintain a strictly heating-focused analytical scope. Indoor thermal comfort was represented using fixed temperature setpoints, with an occupied heating setpoint of 21 °C and an unoccupied setback temperature of 16 °C. These values were applied consistently across all climate cases to support controlled cross-climatic comparison. Heating energy was expressed in terms of delivered thermal demand rather than final system energy consumption. Electricity was used as a reference energy carrier, with a seasonal coefficient of performance (COP) of 1.0 applied to the ideal-loads model. This representation avoids conflating envelope-driven heating demand with assumptions about system efficiency or fuel type, ensuring that the reported reductions reflect passive and solar-responsive performance rather than technological substitutions.

3.7. Optimization Problem Formulation

The optimization problem was formulated as a single objective: the minimization of annual residential space heating load, expressed in kilowatt-hours (kWh). This objective reflects the combined effects of envelope heat transfer, infiltration losses, and useful solar gains, while remaining independent of HVAC system efficiency. By adopting a heating-demand-based objective, envelope-driven performance is isolated and direct interpretation of passive and solar-responsive design behavior is supported.

Design variables were selected to represent parameters that can be adjusted during early design stages and that directly influence heating demand. The window-to-wall ratio was allowed to vary between 20% and 80%, enabling the optimization to explore different degrees of solar aperture. Building orientation was treated as a continuous variable between 0° and 355°, evaluated at 5° increments, while glazing configuration was defined as a discrete variable, including single, double, and triple glazing options as well as high-performance Low-E argon-filled assemblies.

Envelope thermal mass was represented through categorical choices for external wall, roof, and ground floor constructions, classified as lightweight, mediumweight, or heavyweight assemblies. These options capture differences in thermal storage capacity without introducing geometric complexity. Solar control strategies were represented through optional external horizontal overhangs with depths ranging from 0.5 m to 2.0 m, as well as the absence of shading. Internal window controls were modeled through the presence or absence of low-reflective and reflective blinds.

All design variables were evaluated simultaneously within the evolutionary optimization process, allowing interactions among geometry, glazing performance, thermal mass, and solar control to emerge from performance-driven searches rather than from prescriptive assumptions. This formulation enables exploration of a high-dimensional design space while maintaining transparency and relevance to early-stage residential design decisions.

3.8. Optimization Procedure

Simulations were performed in DesignBuilder (Version 7.3.1.003) utilizing the EnergyPlus 9.4 calculation engine. Optimization was implemented using the software's built-in evolutionary algorithm based on NSGA-II, executed in single-objective mode to minimize annual heating demand.

Each optimization run proceeded over multiple generations in which candidate design solutions were iteratively produced through selection, crossover, and mutation. For every candidate configuration, a full annual EnergyPlus simulation was executed, and the resulting annual heating load (kWh/yr) was recorded as the fitness value.

Across the three climate cases, between 96 and 112 candidate solutions were evaluated per optimization run. In the Toronto case, for example, 105 simulations were executed over six generations, corresponding to an average of approximately 17–18 individuals per generation. Similar numbers of simulations were performed for the Riyadh and Barcelona cases. All simulations were performed using DesignBuilder’s default evolutionary settings, including an initial population size of 20 and a maximum population size of 50.

No surrogate models or data-trained predictive algorithms were employed. All optimization outcomes are derived directly from deterministic dynamic simulations in EnergyPlus. Artificial intelligence was therefore implemented in the form of an evolutionary search, enabling structured exploration of a high-dimensional design space rather than predictive learning from historical data. The methodological workflow is illustrated in Figure 2.

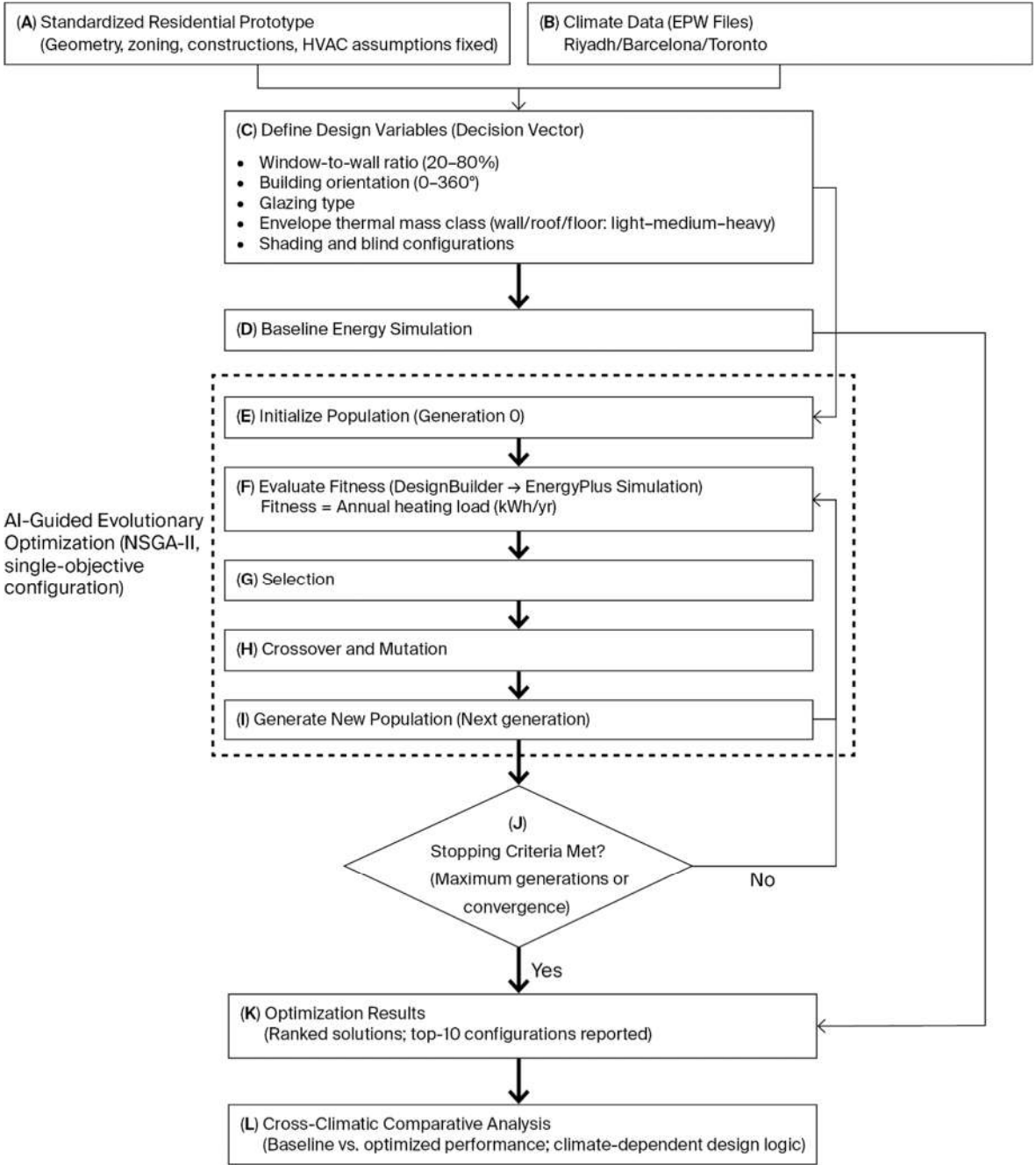


Figure 2. Workflow of the AI-guided evolutionary optimization framework implemented in DesignBuilder (NSGA-II) coupled with EnergyPlus simulations.

3.9. Scope and Limitations

Cooling, domestic hot water, equipment loads, and occupant adaptive behaviors were deliberately excluded from the methodology. Internal gains were maintained constant and identical across climates. The residential prototype does not represent regional construction practices in detail but serves as a controlled comparative model. Accordingly, the results should be interpreted as relative performance improvements under standardized conditions rather than as predictions of absolute real-world energy use.

4. Results

This section presents baseline heating performance and AI-guided evolutionary optimization outcomes for the three selected climatic contexts. The results are first reported for each climate individually, combining narrative interpretation with key quantitative indicators, followed by a consolidated cross-climatic comparison. This structure is intended to emphasize interpretability while avoiding repetition and maintaining analytical clarity.

4.1. Hot and Dry Climate: Riyadh

The Riyadh case represents a hot and dry climate with limited but non-zero winter heating demand. The results illustrate how passive and solar-responsive variables behave when solar availability is high and heating demand is short in duration.

4.1.1. Baseline Heating Performance in Riyadh

Under baseline conditions, the Riyadh residential prototype exhibits very low annual heating demand, reflecting the mild severity and limited duration of winter conditions. The simulated annual space heating load is 989 kWh, corresponding to a heating energy use of approximately 10.5 kWh/m²-yr. Peak heating demand occurs during brief winter periods and remains modest in magnitude compared to the other climates examined. Despite the low baseline demand, heating requirements are not eliminated entirely, indicating that envelope configuration and solar access continue to influence winter comfort even in predominantly cooling-oriented regions.

4.1.2. Optimized Heating Performance in Riyadh

AI-guided evolutionary optimization yields a substantial reduction in heating demand. The best-performing solution reduces the annual heating load to approximately 38.8 kWh, representing a reduction of about 95.9% relative to the baseline. This near-elimination of heating demand is achieved exclusively through passive and solar-responsive design adjustments, without changes to HVAC efficiency or operational assumptions.

Across the highest-performing solutions, the optimization consistently favors increased window-to-wall ratios and orientations that maximize winter solar exposure. High-performance glazing configurations are selected, while shading devices and internal blinds are systematically excluded. These patterns indicate that, under hot and dry winter conditions, maximizing solar gains dominates the optimization logic. Transmission losses remain secondary when cooling is excluded from the objective function. Representative high-performing solutions are presented in Table 2.

Table 2. Top 10 optimized design solutions for the Riyadh case (hot and dry climate), ranked by minimum annual space heating load, obtained through AI-guided evolutionary optimization.

Rank	Heating Load (kWh/yr)	WWR (%) ¹	Rotation (°) ²	Glazing/Window System	External Shading	Internal Blinds	Wall ³	Roof ³	Floor ³
1	38.80	56	165	Double clear glazing, Low-E coating, argon-filled	None	None	L	M	M
2	45.82	56	165	Double clear glazing, Low-E coating, argon-filled	None	None	L	M	H
3	52.30	72	155	Double clear glazing, Low-E coating, argon-filled	None	None	H	H	H
4	54.84	62	165	Triple clear glazing with 1 m louvres	None	None	M	M	M
5	59.13	58	160	Double clear glazing, Low-E coating, argon-filled	None	None	L	M	L
6	59.22	80	155	Double clear glazing, Low-E coating, argon-filled	None	None	M	H	M
7	62.79	62	155	Double clear glazing, Low-E coating, argon-filled	None	None	M	M	M
8	71.49	64	160	Double clear glazing, Low-E coating, argon-filled	None	None	L	M	L
9	76.76	70	160	Double clear glazing, Low-E coating, argon-filled	None	None	M	M	M
10	146.99	36	250	Triple clear glazing with 1 m louvres	None	None	M	M	M

¹ WWR = window-to-wall ratio, ² Rotation in degrees, ³ Wall/roof/floor mass classes derived from the construction labels (lightweight/mediumweight/heavyweight).

4.2. Temperate Climate: Barcelona

The Barcelona case represents a temperate climate characterized by a distinct heating season of moderate severity. The results highlight the balance between solar utilization and transmission loss control under these conditions.

4.2.1. Baseline Heating Performance in Barcelona

In the Barcelona case, the baseline heating demand is substantially higher than in Riyadh, reflecting cooler winter temperatures and a longer heating season. The annual heating load of the baseline model is 5652 kWh, corresponding to a heating energy use of approximately 60.0 kWh/m²·yr. Heating demand is distributed across a broader portion of the year, increasing the importance of envelope thermal performance and heat retention relative to the hot and dry case.

4.2.2. Optimized Heating Performance in Barcelona

Optimization reduces the annual heating demand to 1987.95 kWh, corresponding to a reduction of approximately 64.8% relative to baseline performance. Although the relative reduction is smaller than in Riyadh, the absolute energy savings are substantial. Unlike the hot and dry case, for Barcelona, optimizations consistently favor glazing performance rather than geometric solar amplification alone. High window-to-wall ratios are retained in top-performing solutions only when paired with triple Low-E argon-filled glazing. Orientation continues to influence performance, but its effect is moderated by the dominant role of transmission loss suppression. Representative optimized solutions for the temperate climate case are summarized in Table 3.

Table 3. Optimized design solutions for the Barcelona case (temperate climate).

Rank	Heating Load (kWh/yr)	WWR (%) ¹	Rotation (°) ²	Glazing/Window System	External Shading	Internal Blinds	Wall ³	Roof ³	Floor ³
1	1987.95	78	275	Triple clear glazing, Low-E coating, argon-filled	None	None	M	L	L
2	1987.95	78	275	Triple clear glazing, Low-E coating, argon-filled	None	None	H	M	L
3	2008.60	78	340	Double clear glazing, Low-E coating, argon-filled	None	None	H	M	L
4	2103.88	76	45	Triple clear glazing, Low-E coating, argon-filled	None	None	H	H	H
5	2151.00	68	305	Double clear glazing, Low-E coating, argon-filled	None	None	M	M	M
6	2186.33	76	340	Triple clear glazing, Low-E coating, argon-filled	None	None	H	M	H
7	2206.64	56	185	Triple clear glazing, Low-E coating, argon-filled	None	None	M	M	L
8	2218.80	46	200	Triple clear glazing, Low-E coating, argon-filled	None	None	M	M	L
9	2299.64	74	340	Triple clear glazing, Low-E coating, argon-filled	None	None	H	M	H
10	2506.81	44	190	Triple clear glazing, Low-E coating, argon-filled	None	None	H	M	M

¹ WWR = window-to-wall ratio, ² Rotation in degrees, ³ Wall/roof/floor mass classes derived from the construction labels (lightweight/mediumweight/heavyweight).

4.3. Cold and Humid Climate: Toronto

The Toronto case represents a cold and humid climate with prolonged and heating-dominated winter conditions. This case provides the most stringent test of passive and solar-responsive optimization strategies.

4.3.1. Baseline Heating Performance in Toronto

The Toronto baseline exhibits the highest heating demand among the three cases. The annual heating demand reaches 16,903.94 kWh, corresponding to a heating energy use of approximately 179.4 kWh/m²-yr. Heating demand persists for extended periods throughout the year, and peak loads are significantly higher than those in the other climates. This baseline is a challenging reference condition against which the effectiveness of passive optimization strategies in cold climates can be evaluated.

4.3.2. Optimized Heating Performance in Toronto

Optimization reduces the annual heating demand to 9611.69 kWh, corresponding to a reduction of approximately 43.1%. Although the relative reduction is smaller than those observed for warmer climates, the absolute energy savings are considerable. Optimized solutions consistently feature high-performance glazing combined with heavyweight envelope constructions and limited solar control through short overhangs. Window-to-wall ratios remain moderate, reflecting the need to balance useful solar gains against elevated transmission losses during prolonged cold periods. Representative optimized solutions for the cold and humid climate case are reported in Table 4.

Table 4. Optimized design solutions for the Toronto case (cold and humid climate).

Rank	Heating Load (kWh/yr)	WWR (%) ¹	Rotation (°) ²	Glazing/Window System	External Shading	Internal Blinds	Wall ³	Roof ³	Floor ³
1	9611.69	52	105	Triple clear glazing, Low-E coating, argon-filled	1 m OH ⁴	None	H	L	M
2	10,339.04	46	265	Double clear glazing, Low-E coating, argon-filled	None	None	M	L	M
3	10,417.51	22	225	Double clear glazing, Low-E coating, argon-filled	1 m OH	None	M	L	M
4	10,597.96	30	225	Double clear glazing, Low-E coating, argon-filled	0.5 m OH	None	M	L	M
5	11,009.53	42	220	Triple clear glazing, Low-E coating, argon-filled	2 m OH	None	L	L	L
6	11,147.73	30	235	Double clear glazing, Low-E coating, argon-filled	None	None	M	L	M
7	11,164.08	38	270	Double clear glazing, Low-E coating, argon-filled	None	None	M	L	M
8	11,230.37	30	230	Double clear glazing, Low-E coating, argon-filled	0.5 m OH	None	M	L	M
9	11,262.09	30	235	Triple clear glazing, Low-E coating, argon-filled	1 m OH	None	M	L	M
10	11,410.60	40	235	Triple clear glazing, Low-E coating, argon-filled	0.5 m OH	None	M	L	M

¹ WWR = window-to-wall ratio, ² Rotation in degrees, ³ Wall/roof/floor mass classes derived from the construction labels (lightweight/mediumweight/heavyweight), ⁴ OH = overhang.

4.4. Cross-Climatic Comparison

To enable a consolidated comparison of heating performance across the three climatic contexts, Table 5 summarizes the baseline annual heating demand, best optimized outcomes, and relative reductions achieved through AI-guided evolutionary optimization. In addition to reporting the single best-performing solution for each climate, the table provides an overview of performance ranges among high-performing solutions, supporting interpretation of result robustness beyond isolated optima.

Table 5. Baseline vs. best optimized performance (with top 10 context).

Climate Case	Baseline Heating (kWh/yr)	Best Optimized (kWh/yr)	Reduction (%)	Top 10 Mean (kWh/yr)	Top 10 Range (kWh/yr)
Riyadh	989.00	38.75	96.1	82.7	38.8–147.0
Barcelona	5652.03	1987.95	64.8	2197.1	1987.9–2506.8
Toronto	16,903.94	9611.69	43.1	10,811.7	9611.7–11,410.6

The comparison reveals clear climate-dependent differences in both absolute and relative heating reductions. The hot and dry Riyadh case exhibits the largest relative reduction, reflecting the amplification of winter solar gains on a low baseline heating demand. In contrast, the temperate Barcelona case demonstrates substantial reductions driven by a balance between improved glazing performance and controlled solar access. More constrained relative reductions are achieved for the cold and humid Toronto case, governed primarily by transmission loss control and thermal mass rather than solar amplification alone. These numerical trends are visualized in Figure 3, which illustrates baseline and optimized annual heating demands across the three climates. This figure highlights that passive optimization does not scale uniformly with climatic severity. Instead, through optimization, design priorities are reorganized according to the dominant physical mechanisms governing heating demand in each context, emphasizing solar utilization in mild winters, envelope efficiency in temperate conditions, and loss mitigation in colder climates.

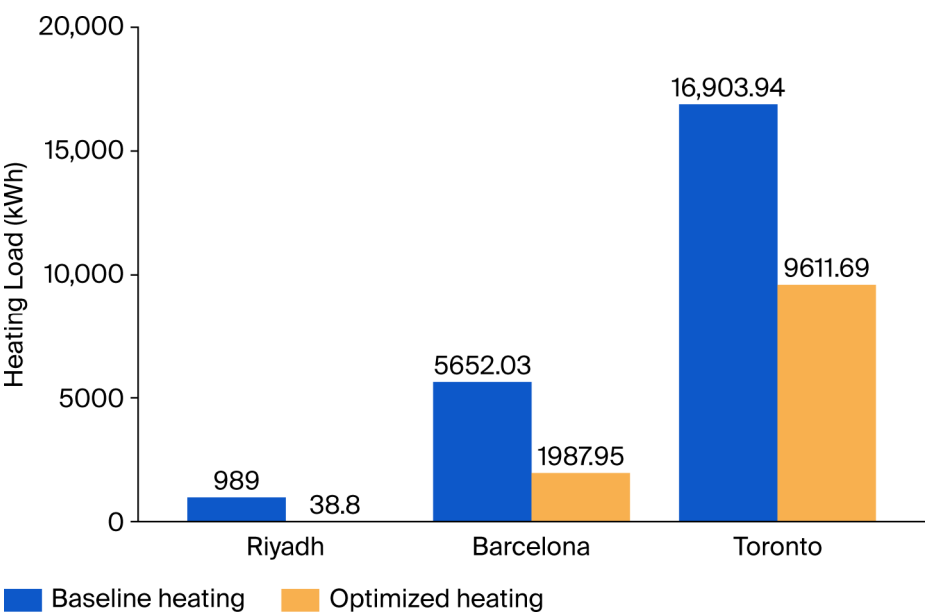


Figure 3. Baseline and optimized annual heating demand across climates.

Additional comparative insight is provided in Figure 4, which illustrates baseline heating demands alongside those of the top ten optimized solutions for each climate case. The figure highlights not only the magnitude of reductions relative to baseline but also the performance dispersion among high-ranking solutions. For Riyadh, there is a steep reduction gradient between the baseline and optimized cases, while for Barcelona and Toronto there are narrower but stable optimization bands, indicating consistent solution clusters rather than isolated optima.

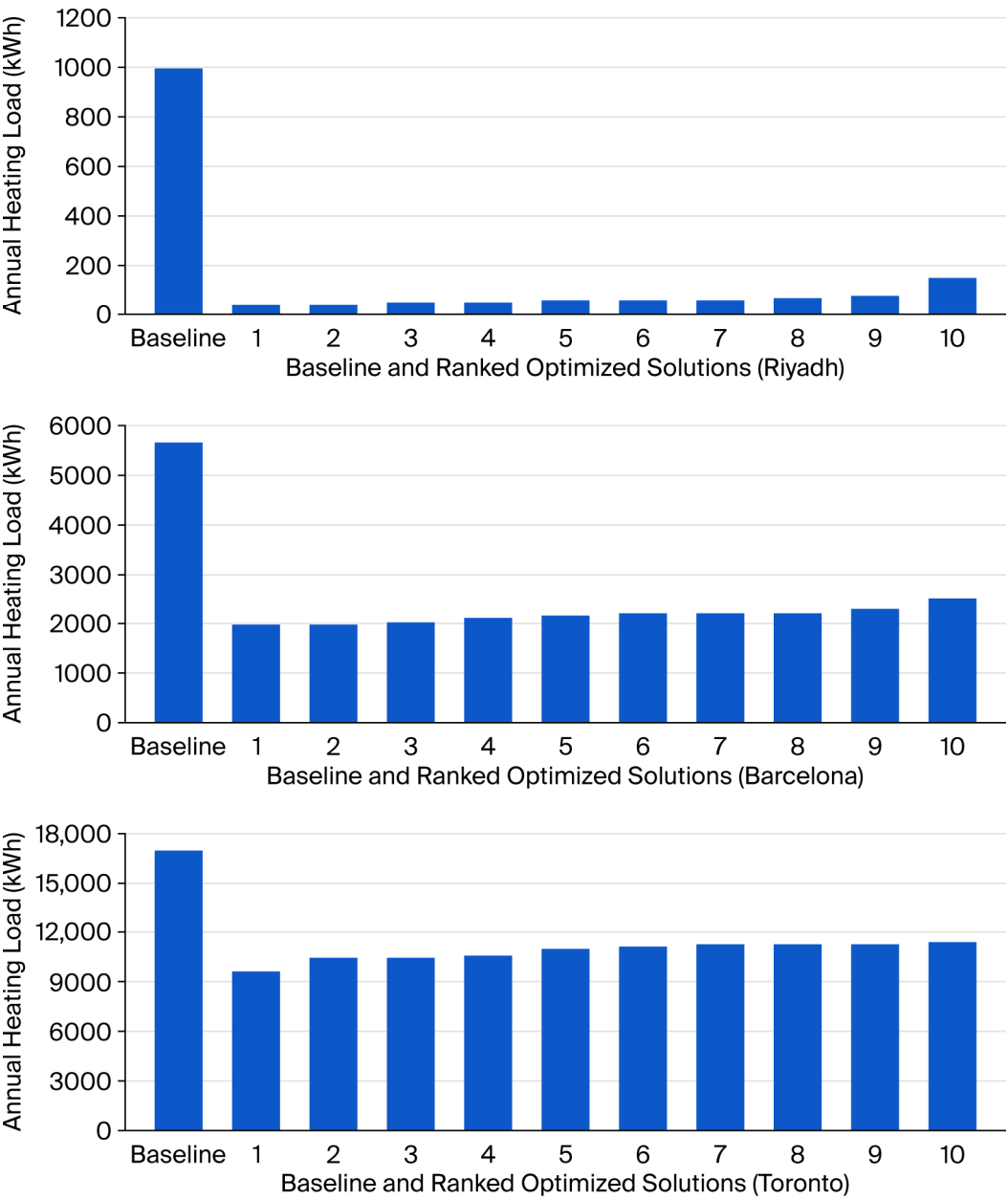


Figure 4. Baseline annual heating demand and top 10 optimized solutions across Riyadh, Barcelona, and Toronto.

4.5. Robustness and Sensitivity Considerations

To evaluate the robustness of the optimization outcomes, a structured sensitivity analysis was conducted on the best-performing solution identified for each climate case. The objective was not to quantify absolute predictive uncertainty, but to test whether the observed climate-specific optimization logic remained stable under moderate variations in key modeling assumptions.

First, infiltration sensitivity was assessed by varying the baseline air change rate (0.7 ACH) by $\pm 20\%$ (0.56 ACH and 0.84 ACH). For the optimized solutions in Riyadh, Barcelona, and Toronto, this perturbation resulted in heating load variations ranging between 6% and 10% relative to the original optimized values. Importantly, the ranking of the top-performing solutions and the dominant envelope strategies remained unchanged across all three climates.

Second, comfort sensitivity was examined by adjusting the occupied heating setpoint by $\pm 1\text{ }^{\circ}\text{C}$ around the baseline value of $21\text{ }^{\circ}\text{C}$. This variation produced heating load changes between 8% and 12%, consistent with the expected thermodynamic sensitivity to setpoint variation. However, no

shifts were observed in the qualitative hierarchy of optimized variables, including window-to-wall ratio ranges, glazing selections, or thermal masses.

Finally, the solution-space stability was evaluated by analyzing the distribution of the top ten optimized configurations per climate. For all three cases, the heating demand of the top ten solutions remained within a 5%–15% band relative to the best-performing configuration. This indicates that the reported results do not represent isolated optima but rather stable performance regions within the explored design space.

Taken together, these tests indicate that the identified climate-dependent optimization logic is robust to moderate variations in infiltration and comfort assumptions. The findings should therefore be interpreted as structurally stable envelope-driven tendencies under heating-focused boundary conditions rather than outcomes dependent on narrowly calibrated parameters.

5. Discussion

In this section, the optimization outcomes are interpreted by examining how dominant passive design variables and their interactions vary across climatic contexts. Rather than reiterating the numerical results, the discussion focuses on the physical mechanisms and design logic that emerged from the AI-guided evolutionary search. Emphasis is placed on explaining why distinct combinations of solar utilization, envelope performance, and thermal storage are favored in different climates and on clarifying the applicability and limitations of the findings.

5.1. Climate-Dependent Optimization Logic

The results demonstrate that AI-guided passive optimization does not converge toward a single universal design solution. Instead, it produces climate-specific optimization logic shaped by the interaction between solar availability, transmission losses, and the severity and duration of the heating season. This outcome aligns with previous research showing that the effectiveness of passive strategies is inherently context-dependent [1,4,8].

In the hot and dry Riyadh case, optimization nearly eliminates heating demand by maximizing winter solar gains through increased window-to-wall ratios and favorable orientations. The magnitude of this reduction reflects the combination of a low baseline heating demand and unconstrained solar amplification under a heating-only objective, rather than a generalizable expectation for real-world residential operation. When cooling requirements, summer overheating risk, or seasonal comfort constraints are reintroduced, the extent of solar amplification that would be feasible is expected to narrow. Nevertheless, the results highlight how responsive a low baseline heating demand can be to envelope configuration and orientation when cooling constraints are deliberately removed. Comparable tendencies have been reported in arid-climate studies, in which winter heating demand could be minimized through solar exposure despite a cooling-dominated annual profile [9,27].

By contrast, the temperate Barcelona case reveals a different hierarchy of influential variables. Although an increased glazing area remains beneficial, optimization shifts toward improving glazing performance rather than maximizing solar aperture alone. The repeated selection of triple Low-E argon-filled glazing indicates that limiting transmission losses while preserving useful solar gains is critical under moderate heating conditions. This behavior is consistent with studies showing that, in temperate climates, envelope efficiency is prioritized over geometric solar amplification in heating optimizations [6,26]. Orientation remains relevant but plays a secondary role compared to the thermal quality of the glazing system.

The cold and humid Toronto case reinforces this progression. Optimization converges toward solutions that combine high-performance glazing with substantial thermal mass and controlled solar admission through limited overhangs. Unlike the hot and dry context, unrestricted solar amplification is not optimal because increasing the glazing area without sufficient thermal resistance elevates heat losses during prolonged cold periods. The presence of short overhangs among top-performing solutions reflects a balance between capturing winter solar gains and limiting losses

during shoulder seasons. Similar findings have been documented in cold-climate studies, in which heating demand is governed primarily by loss reduction and heat storage capacity rather than solar gain alone [2,3,22].

5.2. Role of Window-to-Wall Ratio and Glazing Performance

Across all climates, window-related parameters emerged as central to heating optimization, although their functional role varies significantly by context. In Riyadh, higher window-to-wall ratios primarily function as improved solar collectors. In Barcelona and Toronto, windows act as thermally regulated apertures whose effectiveness depends on advanced glazing performance rather than area alone [28].

These findings reinforce the recent literature indicating that the window-to-wall ratio should not be treated as a monotonic design variable. Its optimal value depends on the glazing quality, climatic severity, and the balance between solar gains and transmission losses [7,29]. AI-guided optimization is particularly effective in resolving this dependency because the window area, orientation, and glazing type are evaluated simultaneously rather than independently [10,11]. As a result, oversimplified optimization outcomes, such as universally minimizing the window area or maximizing solar exposure across all climates, are avoided.

5.3. Thermal Mass as a Climate-Selective Strategy

Thermal mass emerges as a decisive variable primarily in the cold and humid climate case. Heavyweight walls and ground floors are consistently selected, reflecting the stabilizing influence of thermal mass on indoor temperatures and its capacity to retain solar and internal gains over extended heating periods [2,3]. In temperate and hot and dry climates, thermal mass plays a more limited role, suggesting that its contribution to heating demand reductions depends on both the heating season duration and the availability of recoverable gains.

These observations align with earlier findings that varying the thermal mass yields diminishing returns in climates characterized by short or intermittent heating seasons [8,9]. The optimization outcomes therefore reinforce the view that thermal mass should be applied selectively as a climate-responsive strategy rather than a universally effective passive heating solution.

5.4. Implications for AI-Guided Early-Stage Design

From a methodological perspective, this study demonstrates the value of heating-focused, single-objective optimization for analyzing passive design behavior. By excluding cooling and HVAC efficiency from the optimization objective, the evolutionary search isolates envelope-driven trade-offs that are often obscured in multi-objective formulations [13,14]. This approach is particularly relevant during early design stages, when decisions regarding orientation, glazing, and construction systems precede mechanical system specification [24].

At the same time, the results must be interpreted within the limits of the modeling assumptions. The ideal-load heating representation isolates demand but does not capture system constraints, occupant-driven adaptation, or operational control strategies. As emphasized in recent analyses, simulation-based predictions of passive solar performance require cautious interpretation when extrapolated to real-world operation [4]. Nevertheless, the controlled nature of the framework strengthens internal validity and supports meaningful comparative insights across climates. Accordingly, the reported reductions should be interpreted as heating-specific performance outcomes rather than indicators of whole-year energy balance or operational energy use.

5.5. Comparison with Prior AI-Based Optimization Studies

Previous AI-assisted optimization studies in the building energy sector have predominantly adopted multi-objective formulations that combine heating and cooling demands with additional criteria such as thermal comfort, cost, or emissions [13,19]. These approaches are valuable for holistic

performance assessment; however, they often make it difficult to isolate the specific contribution of passive and solar-responsive envelope decisions to reductions in heating demand. In many cases, improvements in heating performance are intertwined with HVAC system efficiency, control strategies, or objective weighting rather than envelope-driven behavior alone.

By contrast, the present study adopts a deliberately constrained optimization formulation focused exclusively on annual space heating demand. Building geometry, comfort conditions, and HVAC representation are kept constant across all climate cases, and cooling is intentionally excluded. This structure enables direct cross-climatic comparison of optimization outcomes and supports clearer interpretation of how evolutionary searches reorganize passive design priorities under different climatic drivers.

The contribution of this work lies in clarifying the climate-dependent logic revealed by AI-guided evolutionary optimization when envelope behavior is examined in isolation, rather than proposing a new optimization algorithm. As such, this study complements existing multi-objective frameworks by providing targeted insights into heating-focused passive design during early design stages, where envelope decisions precede system specifications.

5.6. Limitations and Transferability

The findings are specific to the standardized residential prototype, fixed comfort criteria, and modeling assumptions adopted in this study. Absolute heating loads will vary with building form, occupancy behavior, and regional construction practices. However, the relative trends revealed that solar amplification during hot and dry winters, transmission loss control through advanced glazing in temperate climates, and the combined use of thermal mass and controlled solar admission in cold climates are likely transferable to similar low-rise residential typologies [1,22].

Future research could extend this framework by incorporating stochastic occupancy profiles, adaptive comfort models, or calibrated post-occupancy data. Reintroducing cooling as a secondary objective would enable investigation of seasonal trade-offs under more comprehensive performance criteria and further support the application of AI-guided optimization in real-world design decision-making.

6. Conclusions

This study investigated the potential of using AI-guided evolutionary optimization to reduce residential space heating demand across distinct climate zones by isolating envelope and solar-responsive design variables under standardized conditions. Using a consistent single-story residential prototype and a single-objective optimization framework focused on annual heating load, this analysis compared outcomes for a hot and dry climate (Riyadh), a temperate climate (Barcelona), and a cold and humid climate (Toronto).

The results confirm that passive and solar-responsive design strategies can deliver substantial reductions in residential heating demand across all the examined climates, although both the magnitude of the reductions and the underlying physical drivers vary significantly by climatic context. In the hot and dry case, winter heating demand was nearly eliminated through solar amplification enabled by a favorable orientation, an increased glazing area, and minimal solar restriction. In the temperate case, performance was optimized primarily by reducing transmission loss through high-performance glazing combined with moderated solar apertures. In the cold and humid case, meaningful reductions were achieved through a balanced strategy integrating advanced glazing, increased thermal mass, and controlled solar admission, reflecting the physical limits of passive heating under prolonged cold conditions.

A central contribution of this work lies in demonstrating that AI-guided optimization does not converge toward uniform passive design solutions. Instead, it reveals climate-specific hierarchies of influential design variables that emerge from performance-driven evolutionary searches. By constraining the objective function to annual heating demand and deliberately excluding cooling and HVAC system efficiency effects, the individual effect of envelope-level decisions on heating

performance is clarified. This approach enhances interpretability and demonstrates the value of demand-based optimization for supporting early-stage residential design decisions.

The findings also highlight the continued relevance of passive and solar-responsive design in contemporary residential architectures. Even in climates with severe heating requirements, envelope optimization achieved heating demand reductions exceeding 40% without reliance on active system upgrades. These results suggest that integrating AI-guided passive optimization into early design workflows can lead to more climate-responsive and energy-efficient residential buildings before mechanical systems or advanced technologies are introduced.

This study is subject to several limitations. The results are based on a simplified residential prototype, fixed comfort parameters, and an ideal-load representation of heating demand. Occupant behavior, adaptive comfort, and construction variability were not modeled. Accordingly, the reported reductions should be interpreted as conditional on the stated assumptions and as indicators of relative performance rather than absolute predictions of real-world energy use.

Future research may extend this framework by incorporating adaptive comfort models, stochastic occupancy profiles, and combined heating-cooling objectives, as well as by validating optimization outcomes against measured performance data. Within its defined scope, however, this study provides clear evidence that AI-guided evolutionary optimization offers a robust, transparent, and interpretable approach for reducing residential heating demand across diverse climatic contexts.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
WWR	Window-to-Wall Ratio
HVAC	Heating, Ventilation, and Air Conditioning
EPW	EnergyPlus Weather File
COP	Coefficient of Performance
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers

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