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Multi-Objective Performance Assessment and Pareto Screening of Energy Use, Photovoltaic Generation and Life-Cycle Cost for New Rural Housing Across Five Chinese Cities

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Abstract

Improving building energy efficiency is essential for carbon neutrality. China's rural housing consumes a substantial share of energy, yet cross-regional comparisons of energy and economic performance under consistent conditions remain limited. This study evaluates new rural housing performance in Guangzhou, Hefei, Beijing, Harbin, and Aksu, which span four climatic zones. Six building parameters were combined using a mixed-level orthogonal design to generate design alternatives, which were simulated in BEopt to obtain energy use intensity (EUI), photovoltaic generation (PVG), and relative life-cycle cost (LCC). Pearson correlation and multiple linear regression quantified variable-performance associations, while Pareto screening identified non-dominated alternatives. Furring exterior-wall insulation R-value was negatively correlated with EUI in five cities ($p < 0.001$). PV array azimuth, which co-varies with building orientation, and PV tilt were associated with PVG, whereas the variables most associated with LCC and the size of the Pareto sets varied by city. Across 24 non-dominated solutions, mean EUI decreased by 31.1%, PVG increased by 8.6%, and LCC decreased by 9.5% relative to the baseline. The largest individual improvements were a 49.7% EUI reduction in Beijing, 28.6% PVG increase in competition-based Aksu, and 20.2% LCC reduction in Harbin. These results support regionally adaptive and multi-objective design of new rural housing.

Keywords: new rural housing; building energy use; photovoltaic generation; life-cycle cost; Pareto non-dominated screening

1. Introduction

Against the backdrop of global energy transition and China's carbon-peaking and carbon-neutrality goals, the residential sector needs to reduce operational energy use, increase renewable-energy utilization, and account for economic investment [1,2]. China has a large and widely distributed rural housing stock, much of which consists of low-rise, dispersed, detached buildings [3]. Climatic conditions, economic development, and construction practices jointly influence the energy demand of these buildings and the effectiveness of energy-saving measures [4,5]. As rural revitalization and new rural development continue, greater attention is being given to energy conservation, living conditions, and low-carbon technologies in newly built rural housing [3,6,7]. In this study, new rural housing refers to newly constructed low-rise housing developed through this process, primarily serving rural households and reflecting contemporary local needs and construction characteristics.

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Rural areas across China differ in energy supply, building form, envelope construction, and occupant behavior [5,8,9]. Some existing rural houses still have relatively low energy efficiency and inadequate indoor thermal environments [10,11]. These conditions provide a practical basis for designing new rural housing. Design decisions should respond to local building thermal zones and energy demand through suitable envelope configurations and thermal-performance limits [4,12]. They should also account for changes in energy use and cost and coordinate envelope design with PV systems [4,8]. Low-carbon design therefore requires an integrated assessment of operational energy use, PV utilization, and economic investment in relation to local climate and housing characteristics.

China spans several building thermal zones, with substantial regional differences in outdoor temperature, solar radiation, and heating and cooling demands [12,13]. These differences influence the roles of envelope construction, window-to-wall ratio (WWR), and PV utilization [5,9,14]. Complex terrain can also produce different thermal zones and design requirements within the same administrative region [13]. New rural housing should therefore respond to climate zoning, while specific parameters should reflect local climate, housing characteristics, and actual energy-use patterns [12].

Previous studies have examined how envelope construction, building form, operating conditions, and renewable-energy use relate to housing performance [14,15]. However, they differ in cases, variables, parameter ranges, simulation boundaries, and evaluation indicators, making direct regional comparisons difficult. Some studies jointly assess energy use, PV utilization, and economic performance and connect simulation with variable-association analysis and multi-objective decision-making [16,17]. Further cross-regional work is needed under consistent analytical conditions. Such work should clearly distinguish design-alternative generation, dynamic simulation, variable analysis, and Pareto screening of a finite discrete alternative set.

This study compares new rural housing cases in Guangzhou, Hefei, Beijing, Harbin, and Aksu within a consistent analytical framework. A mixed-level orthogonal experimental design generated the discrete alternatives, and BEopt was used to conduct building performance simulations for energy use intensity (EUI), annual photovoltaic generation (PVG), and relative life-cycle cost (LCC). Pearson correlation analysis and multiple linear regression were used to assess design-variable associations, while Pareto screening identified non-dominated alternatives within each city's finite set. The contribution of this study lies in applying the same design variables, parameter ranges, and performance objectives across five cities in four thermal zones, thereby enabling cross-regional comparisons of the relationships between the same design variables and performance indicators, as well as the identification of Pareto-optimal solution sets for each city.

2. Literature Review

2.1. Energy Performance of Rural Housing Under Different Climatic Conditions

The energy performance of rural housing is jointly influenced by climatic conditions, building form, envelope construction, operating patterns, and economic conditions. Climate largely determines heating and cooling demands, while the other factors further affect the effectiveness and feasibility of energy-saving measures [9,11]. Consequently, the main performance problems and appropriate strategies differ across climatic zones.

In severe-cold and cold zones, residential energy use is dominated by winter heating, and improving envelope insulation is therefore central to reducing heat loss. The selection of construction materials and insulation levels also needs to account for housing characteristics, heating systems, and economic conditions [10,18]. Hot-summer and cold-winter zones have both winter heating and summer cooling demands. Building orientation, WWR, spatial layout, and envelope thermal performance therefore need to be evaluated in terms of annual

energy use [14,15]. In hot-summer and warm-winter zones, greater attention is given to shading, natural ventilation, cooling loads, and PV utilization [9]. In northwestern China, insulation, WWR, attached sunspaces, solar energy utilization, and construction costs need to be considered together [4].

Studies across different regions have consistently considered envelope design, but the reported roles of building form, WWR, insulation configuration, and operating parameters vary. The WWR affects both heat transfer through windows and solar heat gains, and its appropriate value depends on local heating and cooling demands [14]. Insulation measures have a relatively direct effect in heating-dominated regions, whereas annual energy use must be assessed in regions with both heating and cooling demands [3]. Complex terrain may also create different building thermal zones and design requirements within the same administrative region [13]. Specific parameter values should therefore be determined by considering the building thermal zone, housing characteristics, and operating conditions together [12].

Some studies have used field surveys and statistical analyses to identify prevalent characteristics of local rural housing and develop locally representative housing models [7]. However, regional studies differ in their housing cases, variable ranges, and evaluation indicators, and their findings mainly characterize the performance of a specific combination of climate and housing type [4,9,14]. Because simulation results reflect the combined influence of climatic conditions and housing characteristics, it remains difficult to directly compare the direction and relative importance of the same variable or determine its appropriate values across regions.

2.2. Performance Objectives and Design Variables for Rural Housing

Performance evaluation for rural housing has expanded from operational energy use to renewable energy utilization and long-term economic performance [17,19]. EUI represents annual energy use per unit of floor area. Annual PVG reflects electricity-generation performance under a given installed capacity [20]. LCC covers investment, operating, maintenance, and energy costs over the evaluation period [19]. These performance indicators do not always change in the same direction. Envelope and PV configurations may simultaneously affect energy use, electricity generation, and cost [8,19]. The synergies and trade-offs among these objectives therefore need to be examined.

Relevant variables include building form, envelope construction, operating conditions, and PV system parameters. Building orientation and WWR affect envelope heat transfer and the solar radiation entering indoor spaces, thereby changing residential heating and cooling demands [14,15]. Exterior-wall, roof, and window constructions affect residential energy use primarily by changing the thermal performance of the building envelope, and the resulting performance also depends on climatic conditions and housing characteristics [4,10]. Heating and cooling temperature setpoints influence the operation of heating and cooling systems [16]. PV panel tilt affects annual PV generation [20].

Existing studies differ in their variable selection, parameter ranges, and performance objectives [16,17]. The appropriate WWR value depends on heating and cooling demands and solar-radiation conditions [15]. Envelope insulation levels need to be evaluated by considering energy savings, material investment, and long-term economic performance together [3]. Variable selection and the interpretation of variable roles should therefore reflect the evaluation objectives, housing characteristics, and operating conditions.

2.3. Building Performance Simulation and Experimental Design

When many design factors and parameter levels are considered, the number of full-factorial combinations increases rapidly. An orthogonal experimental design selects rep-

resentative combinations of factor levels from the complete set and allows the different factors and levels to be examined in a relatively balanced manner using a limited number of alternatives [21]. The method is used primarily to generate design alternatives, and the conclusions drawn from these alternatives are limited to the predefined factors and levels.

EnergyPlus uses a heat-balance approach to simulate the dynamic operation of building envelopes, indoor thermal environments, equipment, and renewable energy systems [22–24]. BEopt can organize discrete options for residential envelopes, operating conditions, equipment, and PV systems and use EnergyPlus as its calculation engine [25]. Its built-in cost data, equipment lifetimes, and energy prices are based mainly on the U.S. residential market [26]. Without local calibration, the resulting economic outputs are more suitable for relative comparisons among alternatives within the same region.

Existing studies often combine building performance simulations or surrogate models with algorithms such as the Non-dominated Sorting Genetic Algorithm II (NSGA-II) to iteratively search a defined design space and obtain a corresponding Pareto solution set [27,28]. Alternatively, a finite set of design combinations can be generated within a discrete parameter space. After their performance has been calculated, non-dominated alternatives can be identified using Pareto dominance [19,27]. BEopt uses a sequential search process to generate a cost–energy-savings path [25]. Results from finite-alternative screening therefore apply only to the evaluated design space and do not represent a global optimum in a continuous parameter space.

2.4. Research Gaps and Contributions of This Study

Previous studies have examined the performance implications of rural housing envelopes and building forms across different climatic contexts [4,14,15]. Some studies have separately evaluated energy use, PV utilization, and economic performance [8,19]. However, research comparing the three performance objectives and examining their synergies and trade-offs across regions under consistent conditions remains limited. Existing studies also differ in their housing cases, variable ranges, simulation boundaries, and evaluation indicators, making it difficult to compare the role of the same variable across regions [4,9,14]. This comparability limitation is more pronounced when different regions use their respective local housing cases because the results reflect the combined influence of climatic conditions and housing characteristics.

This study addresses this gap by applying a single framework to new rural housing cases in Guangzhou, Hefei, Beijing, Harbin, and Aksu, using the same six design variables, the same mixed-level orthogonal design, the same simulation workflow, and the same three performance objectives. This design generates three elements of new knowledge. First, it provides a directly comparable cross-regional evidence base for the association between the same design variables and the same performance indicators, which previous single-region studies do not provide. Second, it separates the variable-performance associations into those whose direction was consistent across the five cases and those that were case-specific, and thereby quantifies the boundary of transferability rather than describing it qualitatively. Third, it shows that the multi-objective trade-off structure is itself city-specific, in that the size and composition of the Pareto non-dominated sets differed substantially even under a common framework. The results therefore identify which design decisions can be guided by directionally consistent knowledge and which require local calibration.

3. Methodology

3.1. Research Framework

The study comprised five sequential stages: case selection, experimental design, performance simulation, design-variable association analysis, and multi-objective design screening

(Figure 1). (1) Five new rural housing cases reflecting local building characteristics were selected from Guangzhou, Hefei, Beijing, Harbin, and Aksu, considering climatic conditions and the completeness of the available building documentation. These cases provided the building geometry and local housing characteristics required for model development. (2) Six design variables were considered: building orientation, furring exterior-wall insulation R-value, roof surface solar absorptance, south-facing WWR, paired heating and cooling temperature setpoints, and PV panel tilt angle. A mixed-level orthogonal experimental design was used to generate discrete building alternatives for each city. (3) The design alternatives were developed in BEopt (3.0.1.0), and EnergyPlus (8.0.0) was used to conduct building performance simulations. Three performance indicators (EUI, PVG, and relative LCC) were obtained for each alternative. (4) The simulation outputs were used as inputs for Pearson correlation analysis and multiple linear regression. These methods were used to examine the statistical associations between the design variables and performance indicators within the specified parameter ranges. (5) Pareto non-dominated screening was conducted by minimizing EUI and LCC while maximizing PVG. A non-dominated set was identified for each city to examine the synergies and trade-offs among the three performance indicators and compare the design-variable combinations and performance characteristics of the non-dominated alternatives.

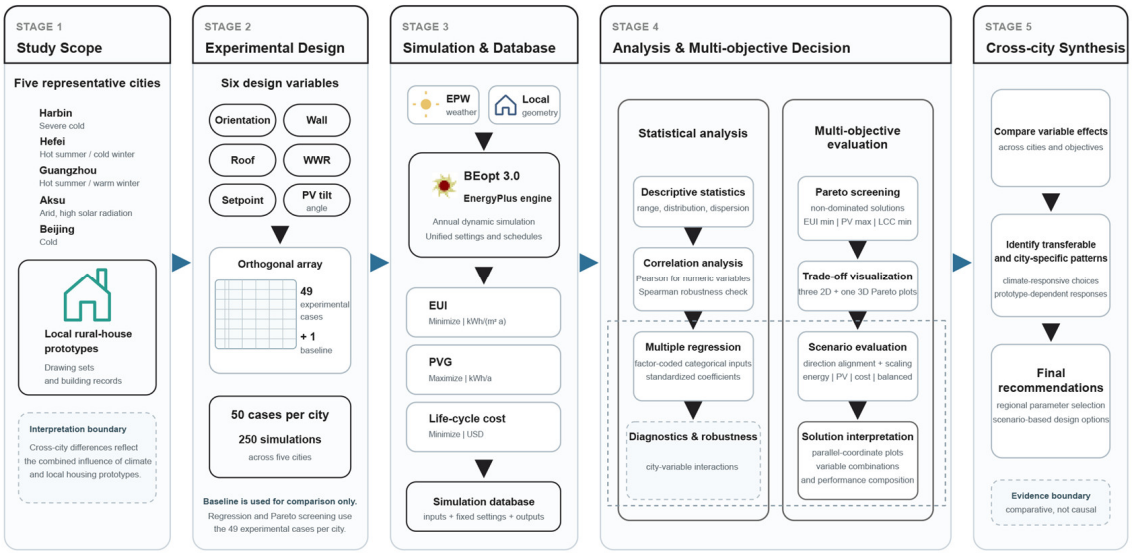


Figure 1. Research framework and analytical workflow.

3.2. New Housing Cases

Following the building thermal zones defined in the Code for Thermal Design of Civil Buildings and considering regional climatic characteristics, Guangzhou, Hefei, Beijing, Harbin, and Aksu were selected as the study areas. These cities cover four building thermal zones: hot-summer and warm-winter, hot-summer and cold-winter, cold, and severe-cold zones. Guangzhou lies in the hot-summer and warm-winter zone, while Hefei lies in the hot-summer and cold-winter zone. Beijing and Aksu are in the cold zone, and Harbin is in the severe-cold zone [12]. Although Beijing and Aksu belong to the same cold zone, their climatic contexts differ. Aksu was included as a cold-arid case to extend the assessment of new rural housing performance to inland northwestern China.

The housing cases for all five cities were obtained from published rural housing design materials for the corresponding regions. The cases for Guangzhou, Hefei, Beijing, and Harbin were selected from the local rural house design atlases [29–32]. These atlases are regional design guidance documents for rural housing, and the selected designs are region-

ally specific and documented in sufficient detail for simulation. The Aksu case was drawn from a public design competition [33]. It is not a built or statistically representative house. Instead, it is included as a contrasting boundary case for a cold and arid climate, broadening the range of case provenance, building form, and climatic context considered under a common analytical framework. Together, the five cases support analytical comparison across selected design archetypes rather than statistical inference about regional housing populations, and they do not capture the full diversity of rural housing in the five regions.

Table 1 lists the source, building form, and floor area of each case, and Figure 2 presents the housing designs and their corresponding BEopt models. Because the five cases differ in building form, floor area, number of stories, and spatial configuration, differences in the simulation results among the cities reflect the combined influence of climatic conditions and local housing characteristics. To characterize this variation, two geometry indicators were calculated for each case and are reported in Table 1, namely the envelope-area-to-floor-area ratio and the surface-area-to-volume ratio. These indicators are included to assess whether the reported cross-city performance differences are consistent with differences in building geometry, which provide descriptive context rather than a basis for separating the effects of building form and climate.

Table 1. Basic information on the new rural housing in the five cities.

City	Climatic Context	Selected Design Case and Source	Building Form	Floor Area (m^2)	Envelope-to-Floor-Area Ratio	Surface-Area-to-Volume Ratio
Guangzhou	Hot-summer and warm-winter region	Guangfu-style row-house Scheme 2 in New Lingnan Style: Atlas of Rural House Design Schemes in Guangdong Province [32]	Two-story row house with a pitched roof	119.50	1.75	0.76
Hefei	Hot-summer and cold-winter region	Scheme 06 in Atlas of Rural House Designs for Anhui's Beautiful and Harmonious Countryside [33]	Two-story detached house with a pitched roof	132.00	2.98	0.89
Beijing	Cold region	Type C in Atlas of New Rural House Designs in Beijing (09BN) [34]	Two-story masonry structure with a pitched roof	175.10	1.97	0.76
Harbin	Severe-cold region	Affordable Type 03 in Atlas of Residential Planning and Architectural Design for Harbin's Socialist New Countryside [35]	Single-story, two-unit row house	199.42	3.11	0.93
Aksu	Cold and arid region	Type 2 in the second "New Era, New Rural Homes" Beautiful Countryside Rural House Design Competition [36]	Two-story house with a pitched roof	165.00	3.36	1.00

Note. The surface-area-to-volume ratio follows the shape-coefficient definition in the Chinese building energy efficiency standard. The envelope area is the external surface in contact with outdoor air; party walls and surfaces in contact with the ground are excluded.



Figure 2. New rural housing cases and their corresponding BEopt models for the five cities: (**a**) Beijing; (**b**) Hefei; (**c**) Guangzhou; (**d**) Harbin; and (**e**) Aksu.

3.3. Simulation Settings and Parameter Inputs

BEopt was used to develop models of the new rural housing cases in the five cities, define the design parameters, and organize the design alternatives. EnergyPlus was used as the calculation engine to conduct annual hourly building performance simulations [22,26]. The weather boundary conditions were obtained from Chinese standard weather data developed for building thermal-environment analysis in Guangzhou, Hefei, Beijing, Harbin, and Aksu. The corresponding EnergyPlus Weather (EPW) files provide the boundary conditions required to simulate building energy use and PVG [34].

All conditions other than the six design variables remained unchanged. These conditions included spatial configuration, occupancy and equipment loads, lighting systems, equipment schedules, and rated PV system capacity (Table 2). The six design variables were building orientation, furring exterior-wall insulation R-value, roof surface solar absorptance, south-facing WWR, paired heating and cooling temperature setpoints, and PV panel tilt angle. Table 3 lists the design variables and their parameter levels.

The five housing cases were derived from publicly available rural housing design atlases and a design competition entry rather than as-built buildings. Case-specific measured energy data were therefore not available. To assess the plausibility of the simulated results, the simulated EUI values were benchmarked against published measured energy-use data for rural housing of a similar type in the same cities or climate zones. This comparison is a plausibility check and not a validation of the simulation model. The models developed here have not been calibrated or validated against measurements from the buildings represented, and the reference cases differ in building form, floor area, occupancy, system boundaries, and data source. PVG and LCC were not benchmarked in the same way: PVG depends strongly on system capacity, tilt, azimuth, roof geometry, and shading, while LCC depends on cost boundaries and economic assumptions that differ across studies. Furthermore,

the PV array was modelled with the specified tilt and azimuth as an unobstructed roof-mounted system. Shading from surrounding buildings, vegetation, and roof components was not represented in the simulations, and the reported PVG values therefore correspond to unobstructed conditions.

Table 2. Main fixed settings shared by the BEopt simulations for the five cities.

Parameter	Type	Setting
Appliances & Fixtures	Clothes Washer	IMEF = 1.57
	Refrigerator	Top freezer, EF = 17.6
	Air Conditioner	COP = 3.6
	Lighting	100% LED
	PV System Capacity	4.0 kW
Construction	Ceiling/Roof	R-value = 5.28 m^2·K/W
	Interior Wall	R-value = 3.00 m^2·K/W
	Floor	R-value = 4.20 m^2·K/W
Window-to-Wall Ratio	West/East	0.3
	North	0.2

Table 3. Design variables and parameter levels used in the orthogonal experimental design and baseline values for the five cities.

Design Parameter	Unit	Parameter Levels in the Orthogonal Experiment	Baseline Value (Case 50)
Building orientation	°	−45, −30, −15, 0 (south), 15, 30, 45	0 (south)
Furring exterior-wall insulation R-value	m^2·K/W	0, 1.76, 2.11, 2.29, 3.35	2.11
Roof surface solar absorptance	-	0.60, 0.70, 0.75, 0.80, 0.85	0.70
South-facing WWR	-	0.30, 0.40, 0.50, 0.60, 0.70	0.50
Heating/cooling set point	°C	(19, 27), (18, 26), (17, 25)	(18, 26)
PV panel tilt	°	30, 45, 60	30

Note: A building orientation of 0° represents due south. Negative values indicate an orientation east of south, while positive values indicate an orientation west of south.

Building energy use was expressed as annual EUI, representing annual operational energy use per unit of floor area. EUI was defined as annual site energy use per unit of conditioned floor area, including heating, cooling, lighting, appliances, and service hot water, but excluding PV generation. PV performance was expressed as annual PVG, representing the annual electricity generated by the PV system. Relative economic performance was represented by LCC. BEopt calculates LCC over a specified analysis period based on the costs and service lives of the design options, energy expenditures, and relevant financial assumptions.

The BEopt cost database, energy prices, and financial assumptions are based mainly on the U.S. residential market [25,26]. The key economic assumptions used for the LCC calculation are listed in Table S1. A 30-year analysis period and a real discount rate of 3% were used, with an inflation rate of 2.4%. Electricity was priced at $0.067/kWh with a fixed monthly charge of $1.66. Exported PV electricity was credited through net metering at $0.067/kWh, and a 30% federal PV tax credit was applied. Initial investment was assumed to be paid in full, and the material and labour cost multipliers were set to unity so the BEopt default cost database and service-life assumptions were applied without adjustment. Table S1 also reports the material cost of each measure associated with the six design variables. Because relative LCC is calculated with reference to the Case 50 baseline, components

that are identical across the 49 alternatives cancel out, and only the measures that vary between alternatives are listed.

These parameters differ from the local material prices, energy prices, and construction conditions of rural housing in China, so the absolute LCC values cannot be interpreted as actual construction costs. Economic performance was expressed as a relative LCC, calculated for each design alternative with reference to the corresponding baseline (Equation (1)):

$$LCC_{rel,i} = (LCC_i - LCC_{ref})/LCC_{ref} \times 100\% \quad (1)$$

where $LCC_{rel,i}$ is the relative LCC of design alternative i, LCC_i is the life-cycle cost of design alternative i and LCC_{ref} is the life-cycle cost of the Case 50 baseline for the same city. Relative LCC was used only for comparisons among alternatives within the same city. Because each city has its own reference value, relative LCC values are also not directly comparable across cities. Cross-city analysis therefore considered only the direction, relative strength, and regional variation in the associations between the six design variables and relative LCC, together with the composition of the non-dominated sets, rather than the magnitude of the LCC values themselves.

Because the default economic assumptions are based on the U.S. market, a sensitivity analysis was conducted to test whether the composition of the Pareto non-dominated sets depends on the assumed ratio between energy-related and material-related costs. The calculated LCC was decomposed into an energy-related component and a non-energy component (Equation (2)):

$$LCC_i = C_{e,i} + C_{m,i} \quad (2)$$

where $C_{e,i}$ is the energy-related component, comprising the present value of heating, cooling, lighting, and appliance expenditures net of PV generation credits. $C_{m,i}$ comprises all remaining costs, including the initial and replacement costs of the envelope, and PV equipment, together with maintenance and other non-energy operating costs. Two alternative scenarios were defined by scaling the energy-related component while holding the non-energy component at its baseline value (Equations (3) and (4)):

$$LCC_i^- = 0.7C_{e,i} + C_{m,i} \quad (3)$$

$$LCC_i^+ = 1.3C_{e,i} + C_{m,i} \quad (4)$$

Equations (3) and (4) change the ratio between the energy-related and material-related components by −30% and +30%, respectively. The Pareto non-dominated screening was repeated for each city under the baseline, the −30%, and the +30% scenarios.

3.4. Orthogonal Experimental Design

When many design factors and parameter levels are included, the number of alternatives required by a full-factorial design increases rapidly. An orthogonal experimental design arranges selected combinations of factors and their levels within a limited number of experimental runs, allowing the different levels of each factor to be examined systematically. This approach improves design-space coverage and simulation efficiency and provides data for comparing the associations between the design variables and performance indicators [21].

Accordingly, a mixed-level orthogonal experimental design was used to generate 49 design alternatives for each city. The six design variables, including building orientation, envelope construction, WWR, air conditioning temperature setpoints, and PV panel tilt, were selected by considering the parameters commonly examined in previous building performance studies [35,36]. In the PV model, the array azimuth was set equal to the building orientation. The orientation variable therefore represents a single setting for both

the building and the array azimuth, and the two cannot be separated within the present design. The panel tilt was specified independently and did not change with orientation.

The levels in Table 3 define the boundary of the parameter space. Building orientation was varied from 45° east to 45° west of south in 15° increments, which covers the most south-facing sector and the orientations over which solar heat gain and building energy use change appreciably. The furring exterior-wall insulation R-value and roof surface solar absorptance represent envelope thermal parameters commonly used in studies of rural building energy efficiency [3], spanning different levels of envelope thermal performance. The south-facing WWR follows the limits in the Chinese standard [37]. The heating and cooling setpoints were treated as three discrete pairs, representing temperature settings that rural households may adopt relative to the standard values [16]. The PV panel tilt was set from the latitude of each climate zone together with previous studies of near-optimal tilt [9]. Because these levels are discrete, the reported associations describe only the evaluated levels and the average trends among them, and values between the tested levels or outside these ranges were not verified.

The six design variables have 7, 5, 5, 5, 3, and 3 levels, giving 7875 full factorial combinations per city. The 49 combinations were generated with the orthogonal design procedure in IBM SPSS Statistics 26.0. The procedure is based on a seven-level orthogonal array and maps the factors with fewer levels onto the array columns. For each city, the orthogonal experimental design comprised 49 design alternatives, as shown in Table S2, each representing a specific combination of the six design variables; these 49 combinations correspond to 0.62% of the full factorial space.

One separate baseline case, Case 50, was simulated for each city using the baseline parameter values listed in Table 3. It serves as an internal reference for expressing the performance of the design alternatives relative to a common starting point within each city. Case 50 was excluded from the correlation and regression analyses because the models were fitted to the 49 alternatives of the orthogonal design, and adding a non-design point would break the orthogonality of the design matrix and change the interpretation of the coefficients. It was also excluded from the Pareto non-dominated screening because that analysis was performed over the 49 evaluated design alternatives, whereas Case 50 is a reference case rather than a design alternative in that set. Thus, 50 simulations were completed for each city. The 49 design alternatives were used in the subsequent statistical analysis and multi-objective design screening, whereas the baseline case was used only for relative performance comparisons. A total of 250 simulations were completed.

3.5. Data Analysis Methods

3.5.1. Pearson Correlation and Multiple Linear Regression Analysis

Pearson correlation analysis was used to examine bivariate linear associations between the six design variables and EUI, PVG, and LCC. Two-sided tests were used to assess statistical significance. Multiple linear regression models were then developed separately for EUI, PVG, and LCC. The heating and cooling setpoints varied as pairs and were coded using the heating setpoint. The multiple linear regression model is specified in Equation (5):

$$Y_i = \beta_0 + \sum_{j=1}^{p} \beta_j X_{ij} + \varepsilon_i \quad (5)$$

where ($Y_{_i}$) is the dependent variable for experimental alternative I; X_{ij} is the design variable j for alternative i; β_0 is the intercept; β_j is a regression coefficient; p is the number of design variables; and ε_i is the random error term. Standardized regression coefficients β were used to remove dimensional differences and compare the direction and relative

magnitude of associations. The regression results report standardized coefficients and their 95% confidence intervals. Adjusted R^2_{adj} was used to evaluate explanatory power.

The correlation and regression analyses quantify statistical association within the sampled design alternatives and do not establish causal relationships. Because the design variables were varied within a simulation model and several potentially relevant factors were held constant or not represented, the coefficients describe the response of the model to the sampled variable levels. They describe average linear trends within the ranges given in Table 3. It should be noted that as the design space is a discrete mixed-level orthogonal set, nonlinear and interaction terms were not included in the reported models, and the 49-run array is not an interaction-resolving design. The coefficients therefore describe the average direction and relative magnitude of the association over the evaluated levels rather than the nonlinear association.

3.5.2. Pareto Non-Dominated Screening

In multi-objective design, different performance objectives generally cannot all attain their respective single-objective optima. A design alternative is Pareto non-dominated if no other alternative can improve at least one objective without worsening any other objective. It therefore represents an efficient trade-off among objectives within the evaluated design set, rather than a unique optimal design. The 49 design alternatives for each city were screened for non-dominance, with EUI and LCC treated as minimization objectives and PVG as a maximization objective. All alternatives not dominated by any other alternative constitute the Pareto non-dominated set. Their distribution in the objective space constitutes the sampled Pareto front within the evaluated set of 49 alternatives [27]. Parallel coordinate plots were then used to compare the design variable combinations and performance indicators of the non-dominated alternatives [38].

4. Results

4.1. Overview of Simulation Results

Figure 3 presents the distributions of EUI, PVG, and relative LCC across the five cities. Because the cases differ in building form and floor area, these performance differences reflect the combined influence of climatic conditions and building geometry, which cannot be separated in the present design. Guangzhou had the lowest mean EUI and a relatively narrow distribution across the 49 design alternatives, whereas Harbin had the highest mean EUI. Compared with Guangzhou, the other four cases showed broader EUI ranges within the discrete parameter space. It should be noted that the Aksu case is a competition-based conceptual design rather than a built or regionally representative house, and the values reported for Aksu describe that design rather than new rural housing in Aksu as a whole.

To provide an external plausibility check, the simulated EUI values were compared with energy-use values reported for rural housing in the same cities or climate zones in previous studies (Table 4). The reported EUI values should therefore be read as comparative and directional results rather than as calibrated absolute predictions for these buildings. Relative to the reference total EUI values, the differences were −10.1% for Guangzhou, −5.4% for Hefei, −8.3% for Beijing, and +7.5% for Aksu. For Harbin, the available reference reported heating energy only, so the comparison was restricted to heating energy. The simulated heating-only value for Harbin is 115.87 kWh/(m^2·year), whereas the mean total EUI reported for Harbin is 169.76 kWh/(m^2·year), which also includes cooling, lighting, appliance, and service hot water energy. The resulting +14.6% difference is therefore not directly comparable with the total-EUI differences reported for the other cities. After boundary alignment, all comparisons were within approximately 15%, indicating that

the simulated EUI values were of a comparable order of magnitude to those reported in previous studies.

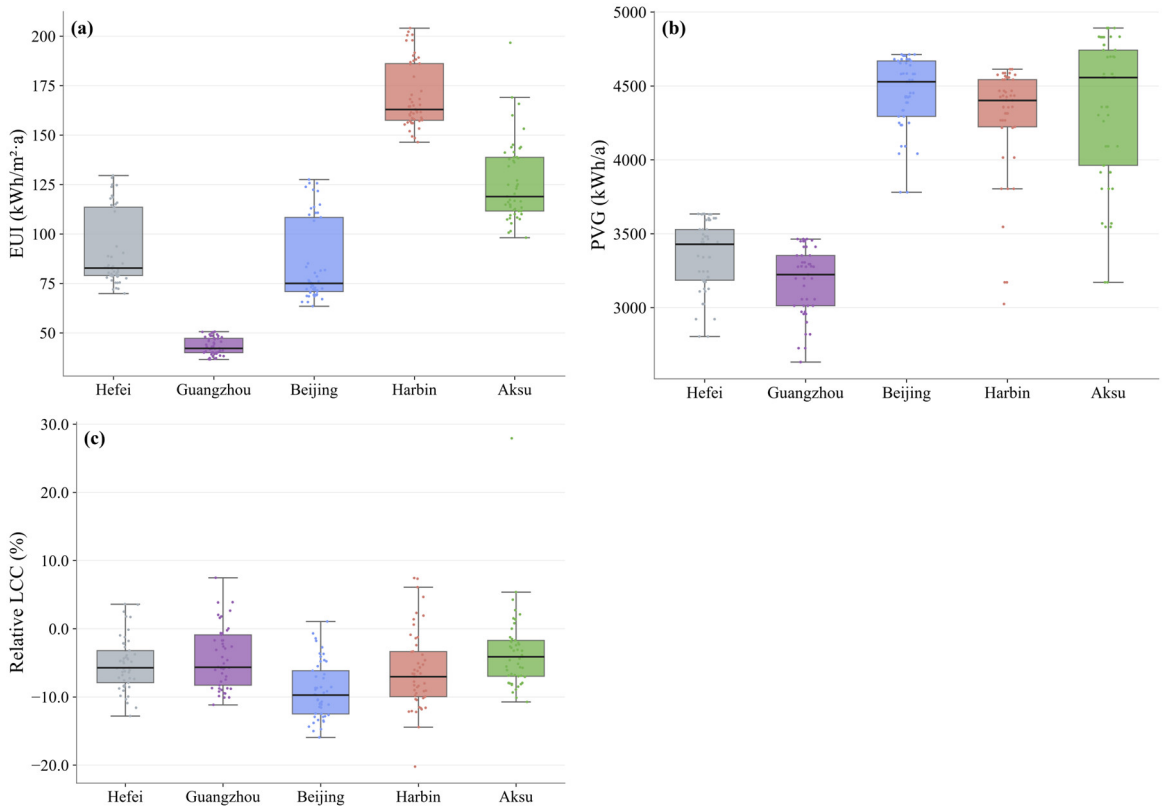


Figure 3. Distributions of the performance indicators across the 49 design alternatives: (**a**) EUI; (**b**) PVG; and (**c**) relative LCC. Note: Relative LCC is the change compared to the Case 50 baseline. Economic assumptions are those of the BEopt default cost database, which is based on the U.S. residential market.

Table 4. Comparison between simulated EUI and reported values from previous studies for rural housing in same climate zones.

City	Simulated EUI (kWh/m²/y)	Reference EUI kWh/(m²·year)	Difference (%)	Reference
Hefei	91.47	96.7	−5.4	[39]
Guangzhou	43.14	48.0	−10.1	[40]
Beijing	85.47	93.2	−8.3	[41]
Harbin	115.87 [a]	101.1 [a]	+14.6	[42]
Aksu	126.10	117.3	+7.5	[43]

[a] Heating-only comparison. Annual total EUI is compared for Guangzhou, Hefei, Beijing, and Aksu. The simulated and reference values for Harbin include space heating only.

The mean PVG values were 3171.76 kWh/year for Guangzhou, 3352.39 kWh/year for Hefei, 4450.20 kWh/year for Beijing, 4267.71 kWh/year for Harbin, and 4346.30 kWh/year for Aksu. Beijing had the highest mean PVG. The maximum PVG in Aksu reached 4891.56 kWh/year, and its standard deviation was the largest among the five cases, indicating greater PVG variability across the evaluated design alternatives.

Relative LCC also varied across the 49 alternatives in each city. Because the BEopt cost database and financial parameters reflect a specific market context, only relative LCC changes and rankings were compared within each city under the same default economic

assumptions. Absolute LCC values were not used to compare the actual economic performance of the housing cases across cities.

4.2. Design-Variable Association Results

The multiple linear regression and Pearson correlation results for the five cities are shown in Figures 4 and 5, respectively. The coefficients describe the statistical association between each design variable and the performance indicator across the sampled alternatives. The association between exterior-wall insulation level and EUI was broadly consistent across the five cities. Pearson correlation analysis showed significant negative correlations in all five cities ($p < 0.001$). The standardized regression coefficients for furring exterior-wall insulation R-value were also negative, and their absolute values were the largest in most of the city-specific models. Thus, within the construction options and parameter ranges considered in this study, higher nominal exterior-wall insulation levels generally corresponded to lower EUI. Furthermore, building orientation was negatively correlated with EUI in Aksu, whereas PV panel tilt angle was positively correlated with EUI in Guangzhou. Roof surface solar absorptance, south-facing WWR, and the paired heating and cooling temperature setpoints did not show statistically significant associations with EUI that were consistent across cities. The standardized regression coefficients for the paired temperature setpoints were positive in Hefei, Beijing, Harbin, and Aksu but negative in Guangzhou. The adjusted R^2 values of the EUI models were 0.87 for Guangzhou, 0.88 for Hefei, 0.85 for Beijing, 0.89 for Harbin, and 0.59 for Aksu.

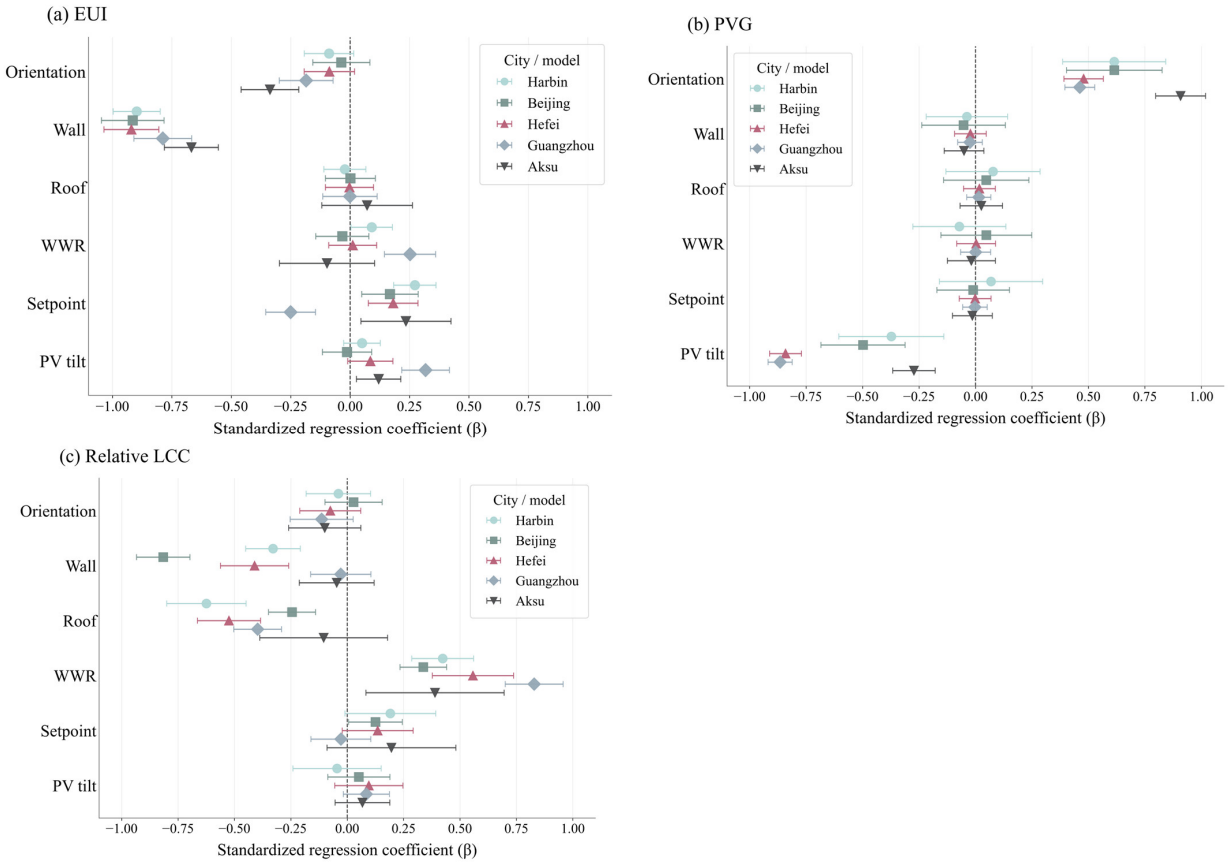


Figure 4. Standardized regression coefficients (β) for the five cities: (**a**) EUI models; (**b**) PVG models; and (**c**) relative LCC models. Note: Relative LCC is the change compared to the Case 50 baseline. Economic assumptions are those of the BEopt default cost database, which is based on the U.S. residential market.

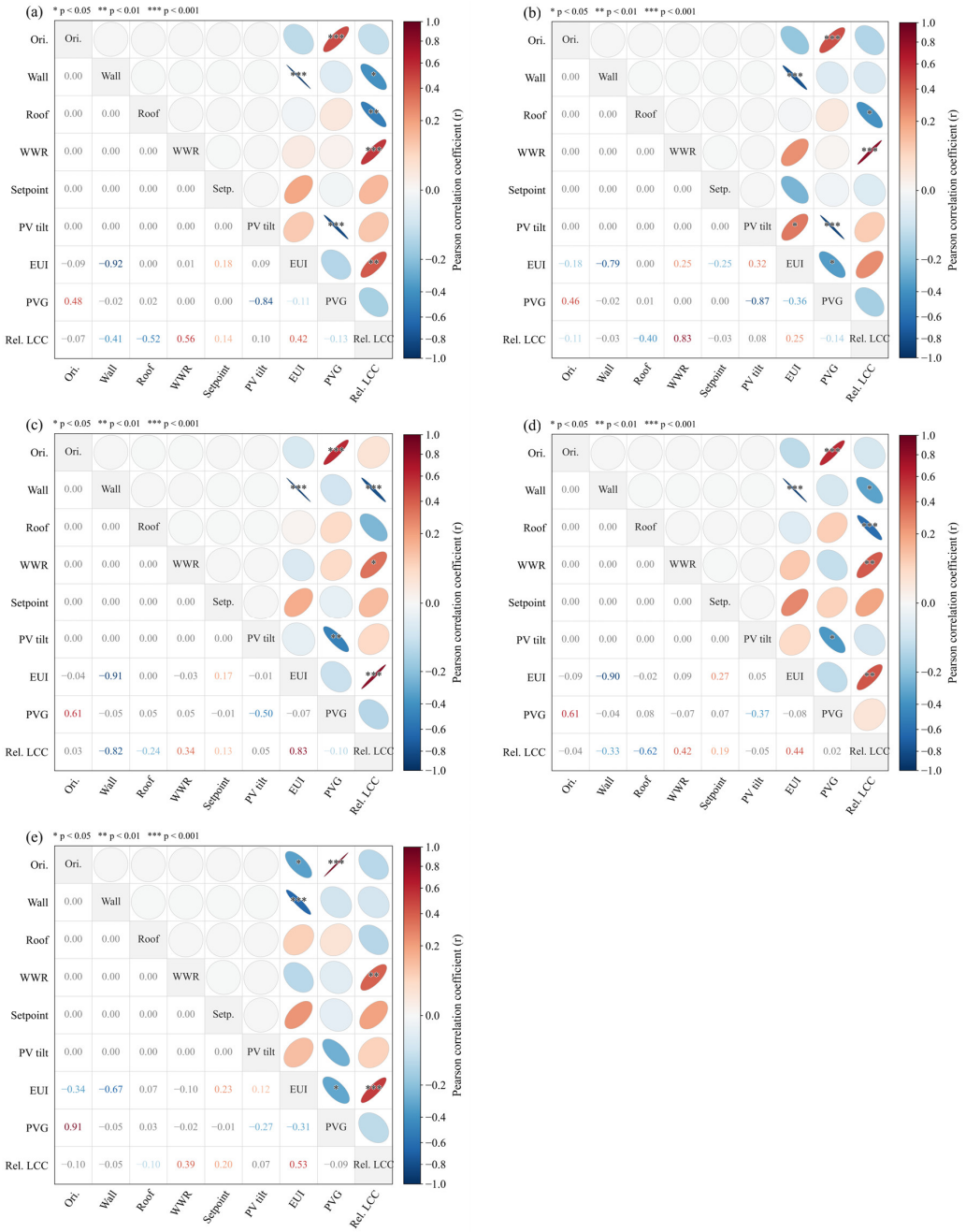


Figure 5. Pearson correlation coefficients between the design variables and the three performance indicators in the five cities: (**a**) Hefei; (**b**) Guangzhou; (**c**) Beijing; (**d**) Harbin; and (**e**) Aksu. Note: Relative LCC is the change compared to the Case 50 baseline. Economic assumptions are those of the BEopt default cost database, which is based on the U.S. residential market.

Building orientation and PV panel tilt angle showed strong associations with PVG, although their correlation coefficients varied across cities. The standardized regression coefficients for building orientation were positive in all five PVG models, whereas those for PV panel tilt angle were negative. The relatively large absolute values of these coefficients indicate that the two variables had comparatively strong associations with PVG. The adjusted R^2 values of the PVG models were 0.96 for Guangzhou, 0.93 for Hefei, 0.58 for Beijing, 0.47 for Harbin, and 0.89 for Aksu. The array azimuth, which co-varies with building orientation in these simulations, and the panel tilt both showed relatively strong associations with PVG, although their coefficients differed across cities. Because the array azimuth follows the building orientation, the coefficient reported for the orientation variable describes

the combined variation in the building orientation and the array azimuth rather than the isolated effect of building orientation.

Under BEopt's default economic assumptions, the variables showing strong associations with relative LCC differed across cities. In Hefei, these variables mainly included south-facing WWR, roof surface solar absorptance, and furring exterior-wall insulation R-value. In Guangzhou, they mainly included south-facing WWR and roof surface solar absorptance. Furring exterior-wall insulation R-value was a variable in Beijing, whereas roof surface solar absorptance was the most prominent variable in Harbin. South-facing WWR was the most prominent variable in Aksu. The adjusted R^2 values of the LCC models for Guangzhou, Hefei, Beijing, and Harbin ranged from 0.68 to 0.85, indicating that the selected design variables explained a relatively large proportion of the LCC variation in these cities.

The associations among the three performance indicators also varied across cities. EUI and LCC were positively correlated in Hefei, Beijing, Harbin, and Aksu, with the strongest correlation observed in Beijing. EUI and PVG were negatively correlated, but the correlations were significant only in Guangzhou and Aksu. Within the design alternatives considered in this study, lower EUI and lower LCC showed some synergy in most cities, whereas the relationships between higher PVG and the other two objectives showed greater variation across cities. It should be noted that the cross-city differences reflect the combined context of climatic conditions, local housing characteristics, and orientation and azimuth settings rather than a climate-only effect.

The adjusted R^2 values of the Aksu EUI model (0.59) and the Beijing (0.58) and Harbin (0.47) PVG models were lower than those of the other models (0.85 to 0.96). Three factors may contribute to this. First, nonlinearity and interaction are not represented in the reported models. PV output responds nonlinearly to both tilt and azimuth, and the tilt that maximizes yield also depends on the azimuth. Because the tilt variable has only three sampled levels, a linear term provides a coarse representation of its association with PVG. This is consistent with the lower PVG R^2 values at the higher-latitude cases of Beijing and Harbin. Second, the PV array was modelled as an unobstructed roof-mounted system, and detailed roof geometry and surrounding shading were not represented, so shading from adjacent buildings, vegetation, and roof components is not captured by the six design variables. Third, several factors are omitted, such as envelope airtightness and thermal bridging details, and the composition of internal loads. For the Aksu case, the reduced documentation associated with a competition-based design may also have prevented full representation of some case-specific envelope and construction characteristics.

For these three models, the lower adjusted R^2 values reduce confidence in the relative magnitudes of the standardized coefficients and in their cross-city comparisons. However, they do not change the fitted signs or invalidate the statistically significant associations reported within the sampled design space. The Pareto non-dominated screening is also unaffected because it uses the directly simulated EUI, PVG, and relative LCC values rather than regression predictions.

4.3. Analysis of Pareto Non-Dominated Alternatives

The Pareto non-dominated screening results for the five cities are shown in Figures 6–10. In these figures, the gray circles represent the 49 design alternatives, the red circles represent the Pareto non-dominated alternatives, and the black crosses represent the separate baseline cases. The non-dominated set for Beijing contained two alternatives; the alternative with higher PVG also had higher EUI and relative LCC. The non-dominated set for Harbin contained the largest number of alternatives and covered the widest range in objective space. These alternatives reflected different performance priorities, including lower EUI, higher

PVG, and lower relative LCC. Among the three non-dominated alternatives in Aksu, the highest PVG did not coincide with the lowest EUI and relative LCC. Across the five cities, lower EUI and lower relative LCC showed some synergy in several alternatives, whereas the maximum PVG generally did not coincide with the minimum EUI and relative LCC.

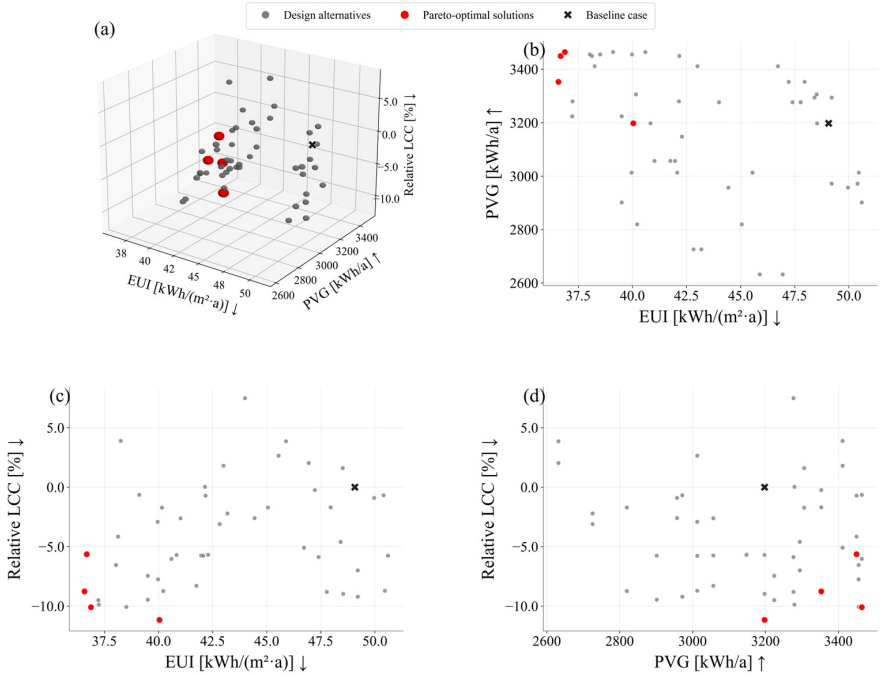


Figure 6. Pareto non-dominated screening results for Guangzhou: (**a**) three-dimensional EUI–PVG–LCC objective space; (**b**) EUI–PVG projection; (**c**) EUI–LCC projection; and (**d**) PVG–LCC projection. Note: Relative LCC is the change compared to the Case 50 baseline. Economic assumptions are those of the BEopt default cost database, which is based on the U.S. residential market.

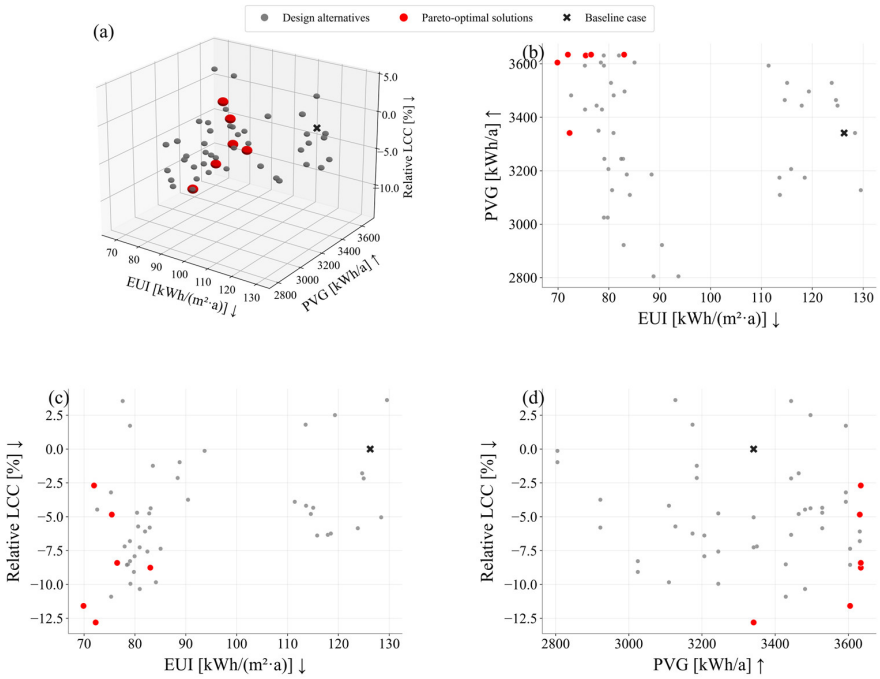


Figure 7. Pareto non-dominated screening results for Hefei: (**a**) three-dimensional EUI–PVG–LCC objective space; (**b**) EUI–PVG projection; (**c**) EUI–LCC projection; and (**d**) PVG–LCC projection. Note: Relative LCC is the change compared to the Case 50 baseline. Economic assumptions are those of the BEopt default cost database, which is based on the U.S. residential market.

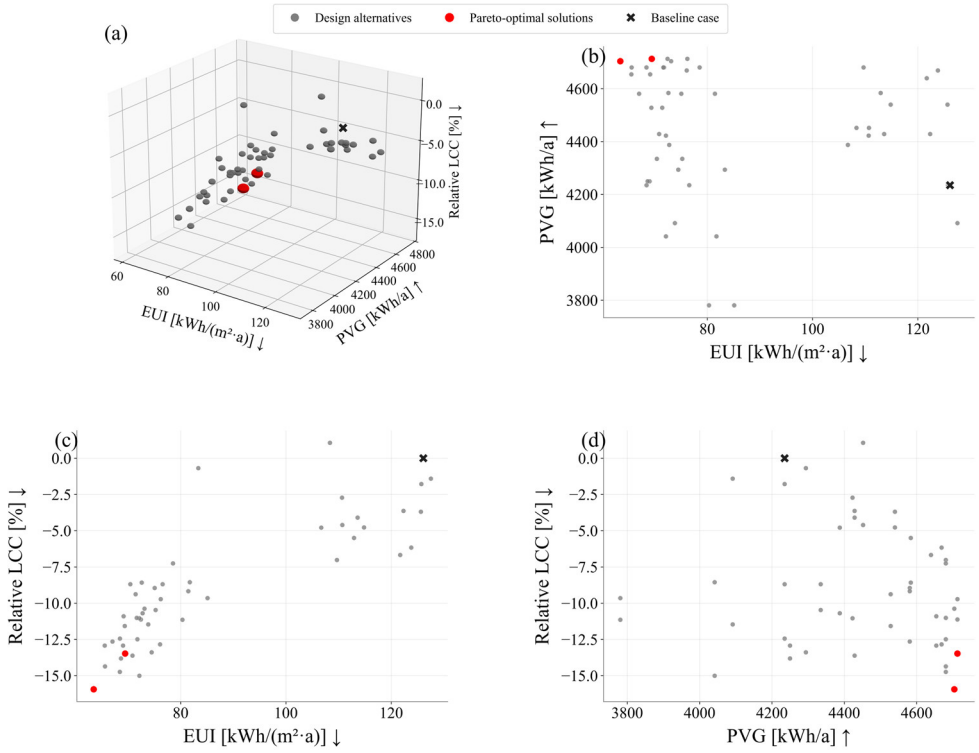


Figure 8. Pareto non-dominated screening results for Beijing: (**a**) three-dimensional EUI–PVG–LCC objective space; (**b**) EUI–PVG projection; (**c**) EUI–LCC projection; and (**d**) PVG–LCC projection. Note: Relative LCC is the change compared to the Case 50 baseline. Economic assumptions are those of the BEopt default cost database, which is based on the U.S. residential market.

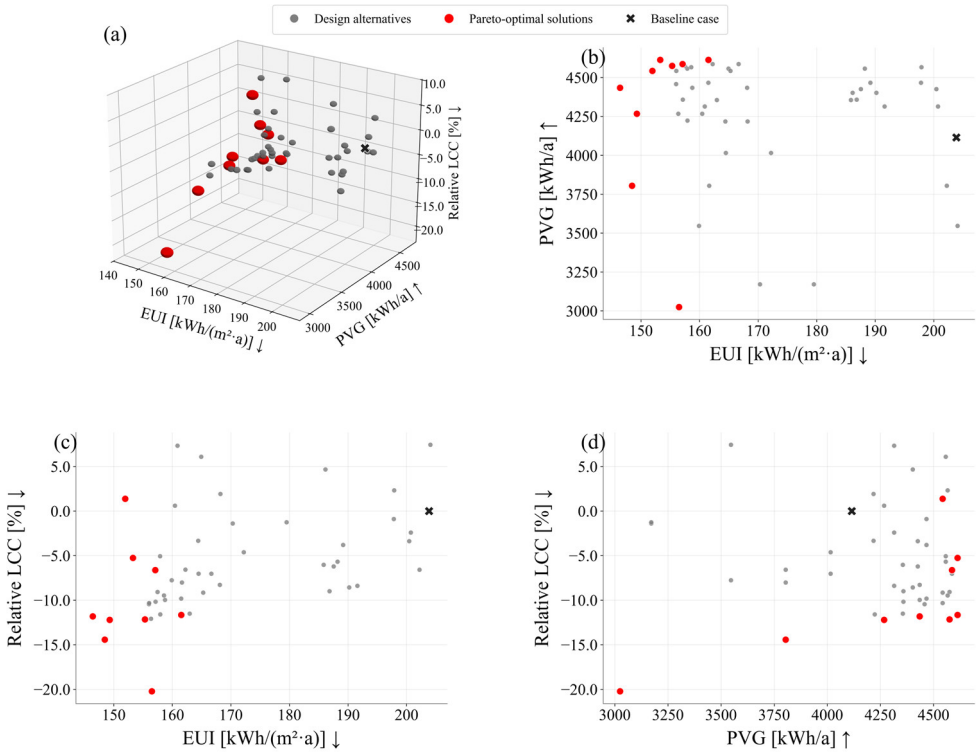


Figure 9. Pareto non-dominated screening results for Harbin: (**a**) three-dimensional EUI–PVG–LCC objective space; (**b**) EUI–PVG projection; (**c**) EUI–LCC projection; and (**d**) PVG–LCC projection. Note: Relative LCC is the change compared to the Case 50 baseline. Economic assumptions are those of the BEopt default cost database, which is based on the U.S. residential market.

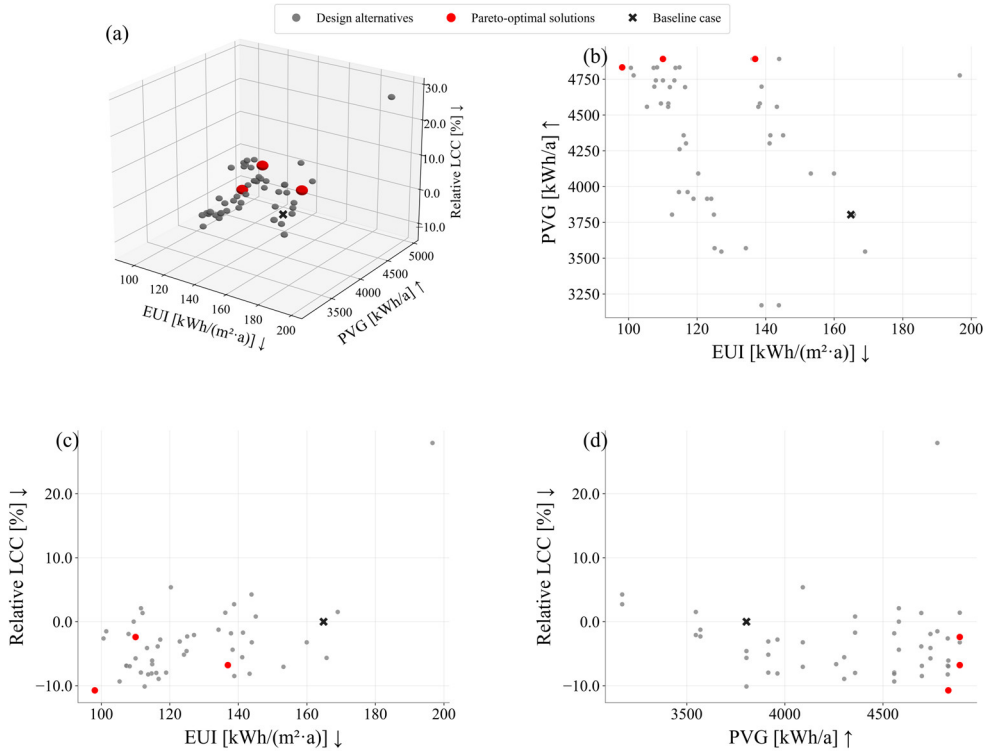


Figure 10. Pareto non-dominated screening results for Aksu: (**a**) three-dimensional EUI–PVG–Relative LCC objective space; (**b**) EUI–PVG projection; (**c**) EUI–Relative LCC projection; and (**d**) PVG–Relative LCC projection. Note: Relative LCC is the change compared to the Case 50 baseline. Economic assumptions are those of the BEopt default cost database, which is based on the U.S. residential market.

Table 5 presents the performance changes of the non-dominated alternatives relative to the corresponding Case 50 baseline in each city. EUI decreased by 17.0% to 49.7%, PVG changed by −26.5% to +28.6%, and relative LCC changed by −20.2% to +1.4%. The largest EUI reduction was 49.7% in Beijing. The largest PVG increase was 28.6%, obtained for the competition-based Aksu case. And the largest relative LCC reduction was 20.2% in Harbin. Some non-dominated alternatives simultaneously reduced EUI and relative LCC while increasing PVG. In other alternatives, improvement in one objective was accompanied by a less favorable change in another, illustrating the synergies and trade-offs among the three performance objectives. It should be noted that the Case 50 baseline is not a typical existing rural house, or a target defined by an external standard. These percentages describe relative differences within the evaluated design set. The gains achievable through an actual renovation would depend on the existing building condition, the scope of the retrofit, construction and transaction costs, and actual occupant behaviour.

To provide a city-specific comparison, Table 5 also reports the mean changes in EUI, PVG, and relative LCC for the non-dominated solutions identified in each city. The results show a difference between the size of the Pareto sets and the average level of improvement. Beijing, with only two non-dominated solutions, had the largest mean reductions in both EUI and relative LCC. Aksu had the largest mean increase in PVG but the smallest mean reduction in relative LCC. Harbin had the largest Pareto set, containing nine solutions, but its mean changes were smaller than those of Beijing, and it therefore contributes the largest number of solutions to the overall average. The solution-weighted means across the 24 non-dominated solutions showed a 31.1% decrease in EUI, an 8.6% increase in PVG, and a 9.5% decrease in relative LCC.

Table 5. Performance changes of the non-dominated alternatives relative to the corresponding Case 50 baseline in each city.

City	Non-Dominated Alternative	Relative Change (%)		
		EUI	PVG	Relative LCC
Hefei	Case 19	−42.8	0.0	−12.8
	Case 35	−40.2	+8.7	−4.8
	Case 37	−34.3	+8.8	−8.8
	Case 40	−43.0	+8.8	−2.7
	Case 42	−39.4	+8.8	−8.4
	Case 47	−44.6	+7.9	−11.6
	Mean	−40.7	+7.2	−8.2
Guangzhou	Case 4	−25.5	+4.9	−8.8
	Case 19	−18.4	0.0	−11.2
	Case 32	−25.3	+7.9	−5.6
	Case 37	−24.8	+8.3	−10.1
	Mean	−23.5	+5.3	−8.9
Beijing	Case 33	−49.7	+11.1	−15.9
	Case 35	−44.9	+11.3	−13.5
	Mean	−47.3	+11.2	−14.7
Harbin	Case 3	−23.2	−26.5	−20.2
	Case 9	−26.8	+3.7	−12.2
	Case 19	−27.2	−7.5	−14.4
	Case 26	−23.8	+11.2	−12.2
	Case 31	−20.8	+12.1	−11.7
	Case 33	−24.8	+12.1	−5.3
	Case 35	−22.9	+11.5	−6.6
	Case 40	−25.5	+10.4	+1.4
	Case 47	−28.2	+7.8	−11.8
	Mean	−24.8	+3.9	−10.3
Aksu	Case 38	−33.3	+28.6	−2.4
	Case 47	−40.5	+27.0	−10.7
	Case 48	−17.0	+28.6	−6.8
	Mean	−30.3	+28.1	−6.6

Note: Relative LCC is the change compared to the Case 50 baseline. Economic assumptions are those of the BEopt default cost database, which is based on the U.S. residential market.

Figure 11 further presents the design parameter combinations and performance characteristics of the non-dominated alternatives. The reported LCC changes were calculated relative to Case 50 baseline under BEopt's default economic assumptions and were used only for relative economic comparisons among alternatives within the same city.

To test the sensitivity of the Pareto results on the assumed economic structure, the Pareto non-dominated screening was repeated for each city under −30% and +30% changes in the energy-to-material cost ratio. Under the +30% scenario, the non-dominated sets were identical to the baseline in all five cities. Under the −30% scenario, the sets for Hefei, Beijing, and Aksu were also unchanged, whereas Guangzhou and Harbin each contained one additional non-dominated solution, increasing their set sizes from 4 to 5 and from 9 to 10, respectively, and no solution was removed. The corresponding changes in the mean values of the revised sets are reported in Table 6. Overall, the composition of the Pareto sets was largely insensitive to the assumed energy-to-material cost ratio. Although the non-dominated sets remained largely stable, their economic composition should be re-evaluated with local material, equipment, energy, and financial data before the results are used for design or policy decisions.

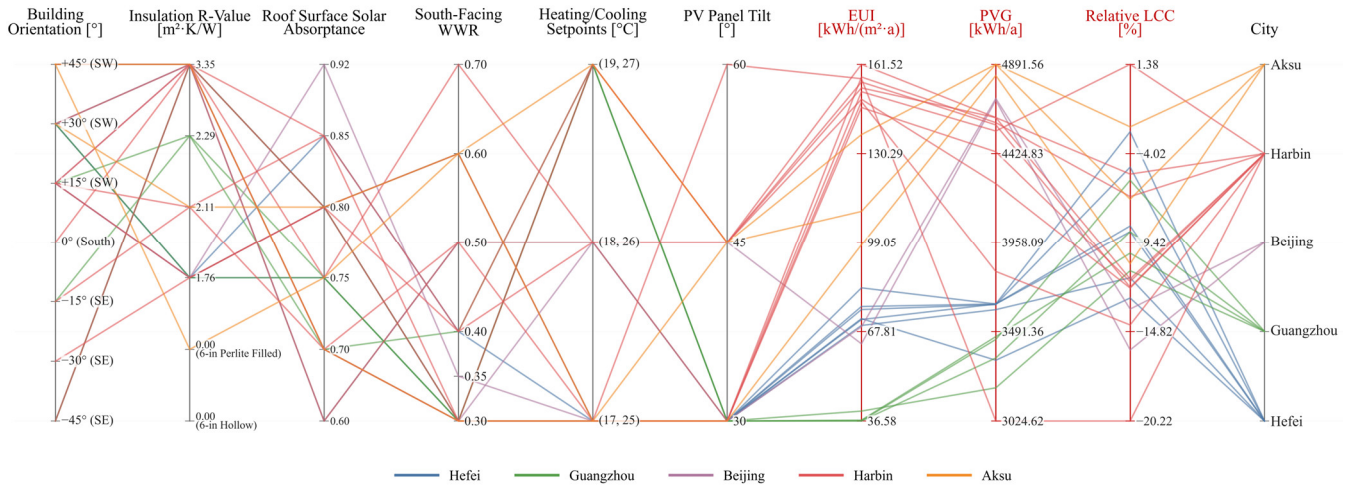


Figure 11. Parallel coordinate plots of design variables and performance objectives for the Pareto non-dominated alternatives in the five cities. Note: Relative LCC is the change compared to the Case 50 baseline. Economic assumptions are those of the BEopt default cost database, which is based on the U.S. residential market.

Table 6. Composition of the Pareto non-dominated sets under ±30% changes in the energy-to-material cost ratio.

City	Number of Non-Dominated Solutions			Mean Performance Under −30%
	Baseline	+30% Scenario	−30% Scenario	
Hefei	6	6	6	Unchanged
Guangzhou	4	4	5	EUI: 37.74 kWh/(m^2·y); PVG: 3383.94 kWh/y; Relative LCC: −8.8%
Beijing	2	2	2	Unchanged
Harbin	9	9	10	EUI: 153.62 kWh/(m^2·y); PVG: 4272.86 kWh/y; Relative LCC: −9.13%
Aksu	3	3	3	Unchanged

Note: Relative LCC is the change compared to the Case 50 baseline. Economic assumptions are those of the BEopt default cost database, which is based on the U.S. residential market.

5. Discussion

5.1. Comparison with Previous Studies

The EUI results and their statistical associations with the design variables showed both common patterns and city-specific differences across the five housing cases. The furring exterior-wall insulation R-value variable was significantly negatively correlated with EUI in all five cities, and the absolute values of standardized regression coefficients were relatively large in most city-specific models, particularly in Hefei, Beijing, and Harbin. These findings are consistent with previous studies of rural housing envelopes, which showed that improving the thermal performance of exterior walls and other envelope components generally reduces heating or annual operational energy use [10,14,18]. By contrast, the directions and strengths of the associations between EUI and building orientation, south-facing WWR, roof surface solar absorptance, and the paired heating and cooling temperature setpoints varied across cities. No consistent cross-city pattern was observed for these variables.

Building orientation and PV panel tilt angle showed comparatively strong associations with PVG, although the strength of these associations varied across the five cities. This finding is broadly consistent with previous research showing that appropriate PV tilt

angles vary across climatic regions and installation orientations [20]. Larger tilt angles generally corresponded to lower PVG. This pattern represents only an average statistical trend within the specified discrete range and does not imply that the same linear relationship applies beyond it. The cross-city differences may be related to solar altitude, solar radiation, and the combined configuration of building and PV orientations. However, because the housing cases also differed in building form, the observed differences cannot be attributed to climatic conditions alone. They also reflect differences in floor area, spatial configuration, and envelope construction among the five cases. Practical designs should therefore be evaluated accounting for roof geometry and surrounding shading. Because shading from adjacent buildings, vegetation, and roof components was not represented in the simulations, the PVG values reported here correspond to unobstructed conditions and should be read as an upper-bound estimate. Shading reduces the irradiance received by the array, and its effect is strongest at low solar altitudes and varies with tilt and azimuth, so it can change the relative influence of the tilt variable and shift the apparent optimal tilt away from the values obtained here. These effects are likely to be more pronounced in dense settlements and in row-house configurations, where neighbouring units reduce the sky view of the roof. For building-integrated photovoltaic (BIPV) systems, module orientation and tilt, local shading, envelope integration, and operation and maintenance should also be considered together during design [44].

Under BEopt's default economic assumptions, Pareto non-dominated screening showed that some alternatives simultaneously reduced EUI and relative LCC while increasing PVG, whereas for other alternatives, improvement in one objective was accompanied by a less favorable change in another. Similar studies have also shown that no single alternative is generally optimal for all decision preferences and that non-dominated sets are more suitable for presenting the synergies and trade-offs among objectives [19,45].

5.2. Physical Mechanisms Underlying the Regional Differences

The regional differences in the EUI associations are consistent with the shift in the balance between heating and cooling demands across the climate zones. Higher exterior-wall insulation reduces conductive heat loss in winter and heat gain in summer in all five cases, which explains the consistent direction of the insulation–EUI association, whereas its magnitude was smallest where the heating season is short and a smaller share of annual demand is sensitive to wall conduction. Larger south-facing glazing increases useful solar gains in heating-dominated cases but raises the cooling load where cooling dominates, and higher roof solar absorptance raises the roof surface temperature, increasing cooling demand while slightly reducing heating demand. The reversal of the setpoint association in Guangzhou has a specific basis: because the heating and cooling setpoints were varied as fixed pairs, a higher coded value raises both, and in a cooling-dominated case, the reduction in cooling demand outweighs the increase in heating demand.

For PVG, the array azimuth, which co-varies with building orientation, and panel tilt were the dominant variables in all five cities, although their relative importance varied with latitude. This pattern is consistent with solar geometry: panel tilt determines the seasonal balance between summer and winter irradiance, while azimuth determines the incidence angle and the time of day at which the array receives maximum irradiance. In general, flatter tilts favour summer generation, whereas steeper tilts favour winter generation. For relative LCC, the variables showing the strongest associations differed among cities. Unlike PVG, relative LCC is not governed by a single physical process; it reflects the balance between discounted energy-cost savings and the initial and replacement costs of the design measures. Because the energy-related component depends on the level and seasonal profile of energy

demand while the material component does not, the variables most strongly associated with relative LCC differed according to which component dominated.

Because the PV array azimuth followed the building orientation in the simulations, the orientation coefficient in the PVG models does not represent the effect of building orientation alone. Under the modelling conditions of this study, the PV system was roof-mounted and no shading was modelled, so building orientation affected PVG through a single channel, namely the change in the azimuth of the array. The coefficient is therefore an estimate of the average effect of the array azimuth, which co-varies with the building orientation, rather than of the isolated effect of building orientation. Three interpretive limits follow. First, the coefficient cannot answer the question of how PVG would change if the array azimuth were held fixed while the building was rotated because such configurations were not simulated. Second, when the relative importance of orientation and tilt is compared, the orientation variable carries both the building rotation and the array rotation so its magnitude should not be interpreted as the pure effect of building orientation. Third, the results apply to configurations in which the array azimuth follows the building orientation. For systems whose azimuth can be set independently, such as flat-roof racks or adjustable-azimuth arrays, the present results do not support design recommendations.

The geometry indicators do not fully account for the ordering of the cases by EUI. Guangzhou and Beijing have the same surface-area-to-volume ratio but differ substantially in mean EUI (43.14 and 85.47 kWh/(m^2·year), respectively), whereas Harbin has the highest mean EUI (169.76 kWh/(m^2·year)), although its surface-area-to-volume ratio is lower than that of Aksu. The ordering of the cities by EUI is therefore broadly, but not strictly, consistent with their geometry. Because each city is represented by a single case, these comparisons remain qualitative, and the influence of building form cannot be separated from that of climate.

5.3. Pareto Trade-Offs and Practical Implications

Comparing the five cities reveals a clear distinction between directionally consistent and city-specific associations. Given that each city is represented by a single housing prototype and that climate co-varies with housing form, these findings support directional consistency within the evaluated cases. The cities differed in the structure of their Pareto trade-offs. EUI and LCC were synergistic in four cities but not in Guangzhou, and EUI and PVG were significantly negatively correlated only in Guangzhou and Aksu. These differences are likely related to the heating–cooling balance, climate severity, building form and floor area, and the fixed operational and economic assumptions used in the simulations. For example, the heating-dominated climates of Harbin and Beijing may strengthen the association of insulation and panel tilt with the performance indicators, whereas the cooling-demand-dominated climate of Guangzhou may weaken the EUI–LCC link and alter the PV trade-offs. Because building form and floor area also differed among the cases, these explanations remain hypotheses rather than isolated climate effects.

Within the sampled ranges, the results support three categories of practical guidance. First, the insulation–EUI and PV tilt–PVG relationships were directionally consistent across the five cities and can inform preliminary design direction. Second, the array azimuth–PVG relationship was directionally consistent only within the coupled orientation–azimuth configuration and cannot be interpreted as an isolated effect of building orientation. Third, heating and cooling setpoints, south-facing WWR, roof surface solar absorptance, and economic parameters require local calibration. The setpoint association reversed in Guangzhou, and the variables most strongly associated with relative LCC differed by city, with south-facing WWR most prominent in Aksu, roof absorptance in Harbin, and furring insulation in Beijing. Even for the directionally consistent relationships, association strength and optimal

values require local determination: the standardized insulation coefficient ranged from −0.92 to −0.67 and was particularly prominent in Hefei, Beijing, and Harbin, whereas PV tilt was more prominent in Beijing and Harbin and array azimuth in Guangzhou and Aksu.

5.4. Limitations and Future Work

First, the study used one design-based archetype per city, which is not a statistically representative sample and cannot capture the full diversity of rural housing in the respective regions. Future work should extend the framework to built and regionally representative cases, and to multiple cases within each region. To ensure comparability among the design alternatives within each city, occupant behaviour, equipment loads, and operating schedules were held constant in the simulations. Actual rural households vary considerably in occupancy, equipment use, and heating and cooling behaviour, and occupant behaviour is a major source of uncertainty in building energy simulation [46]. Because monitored residential heating and cooling behaviour is typically intermittent rather than continuous, the simulated EUI values correspond to a standard operating pattern and may differ from those of occupied houses, and the strength of the reported variable associations may also differ. Future work should therefore incorporate stochastic occupancy and behaviour profiles and behaviour-sensitive sensitivity analysis. Only a plausibility check was performed for the models, rather than validation using case-specific measurements. Calibration with measured data from built rural houses is required before the absolute EUI values are used in practice.

Second, climate was confounded with housing form and floor area because each city was represented by a different housing case. Consequently, the cross-city differences reflect the combined influence of climatic conditions and housing characteristics and cannot be interpreted as climate-only effects. Future work should simulate a common building archetype across the five climatic zones, or include multiple archetypes within each climate zone, to separate climate effects from housing-case effects.

Third, the BEopt cost database, energy prices, and financial assumptions are mainly based on the U.S. residential market. LCC was therefore used only for relative comparisons among alternatives within the same city. Its absolute values and alternative rankings require further validation using local cost data from China. Future research could improve the economic assessment by incorporating local material prices, equipment costs, energy prices, and financial parameters. Replacing the default economic assumptions with local material prices, energy prices, and financial parameters remains necessary before the economic results are applied in practice. The LCC rankings obtained in this study are valid only under the assumptions used here.

Fourth, two related limitations concern the PV model. Because the array azimuth was set equal to the building orientation, their contributions cannot be separated with the present specification. Future work should treat them independently, either by holding the array azimuth fixed while varying the building orientation or by including azimuth as a separate factor. In addition, no shading from surrounding buildings, vegetation, or roof components was modelled. The reported PVG values therefore represent an unobstructed upper bound, and the association with tilt may differ under shaded conditions. A three-dimensional roof and site model or a dedicated solar-access analysis, validated with measured PV yield data, would be required to quantify these effects.

6. Conclusions

Using a consistent framework, this study evaluated 49 design alternatives for five new rural housing cases in Guangzhou, Hefei, Beijing, Harbin, and Aksu. Six design parameters were varied in a mixed-level orthogonal design, and BEopt simulations provided EUI, PVG,

and relative LCC. Pearson correlation, multiple linear regression, and Pareto screening were then applied. The main conclusions are as follows:

(1) Furring exterior-wall insulation R-value was significantly negatively associated with EUI in all five cities. The associations of building orientation, south-facing WWR, roof surface solar absorptance, and heating/cooling setpoints on EUI varied in direction and strength across cities, indicating that these parameters require climate- and case-specific evaluation.

(2) Under the unobstructed roof conditions model, PVG was determined mainly by the array azimuth, which co-varies with building orientation, and by the panel tilt, although their relative importance varied by city. The azimuth coefficient therefore represents their combined effect rather than building orientation alone. The variables most strongly associated with relative LCC were city-specific. The three objectives did not always change in parallel: EUI and relative LCC were positively correlated in four cities but not Guangzhou, whereas PVG showed no consistent association with the other objectives.

(3) Within the evaluated 49-alternative set, the Pareto fronts contained 4, 6, 2, 9, and 3 non-dominated alternatives in Guangzhou, Hefei, Beijing, Harbin, and Aksu, respectively. Across all 24 non-dominated alternatives, mean EUI and relative LCC decreased by 31.1% and 9.5%, while PVG increased by 8.6% relative to the Case 50 baseline. The largest EUI reduction occurred in Beijing, the largest PVG increase (28.6%) occurred in competition-based Aksu, and the largest relative LCC reduction (20.2%) occurred in Harbin.

(4) Within the sampled ranges, three categories of guidance emerge. Insulation–EUI and PV tilt–PVG were directionally consistent and can inform preliminary design, whereas array azimuth–PVG was consistent only within the coupled orientation–azimuth configuration. Setpoints, WWR, roof absorptance, and economic parameters require local calibration. Even for the directionally consistent relationships, association strength and optimal values should be determined locally.

These findings may help designers balance the objectives of reducing operational energy use, increasing PV generation, and improving relative economic performance during the design stage. However, each city was represented by one distinct housing case. The reported city-specific differences therefore reflect the combined influence of climatic conditions and housing characteristics. The findings apply to the evaluated housing cases, model boundaries, and discrete parameter ranges and do not isolate a climate-only causal effect or represent globally optimal solutions in a continuous design space.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/buildings16214391/s1, Table S1: The parameter settings of life-cycle cost in BEopt; Table S2: Orthogonal experimental design for new rural housing cases of five cities.

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