

AI EMPOWERED INTELLIGENT SURVEYING AND MAPPING DRIVES VISUAL REFORM OF MAXIMUM ENTROPY MODELING FOR GREEN ENERGY BUILDINGS

WANG Kai¹, LI YuanCheng^{2*}

Guangxi Construction Vocational College, Nanning, China
Guangxi Vocational Normal University, Nanning, China
*425930191@qq.com

Keywords: Intelligent Surveying and Mapping, AI Empowerment, Green Energy Building, Maximum Entropy Modeling, Visual Reform

Abstract

Popular near-zero energy and BIPV buildings reveal critical drawbacks of classic interpolation: weight bias, low fitting accuracy, incomplete spatial reconstruction and inadequate visual outputs, failing advanced green building design and low-carbon operation. This work differentiates full-cycle AI mapping from conventional survey, numerical optimization and static visualization via automated data collection, adaptive iteration and real-time 3D rendering. A joint framework combining cross-entropy calibration, maximum entropy modeling and genetic optimization is built to resolve the Yang Chizhong method's negative weight distortion and unstable convergence. Ten repeated ablation experiments on Nanning green building projects adopt mean and standard deviation statistics for validation. The proposed method fully erases negative weight distortion, reduces energy RMSE by 23.6 percent, boosts radiation fitting accuracy by 18.9 percent and improves weight convergence stability by 31.2 percent. Quantitatively evaluated AI visualization tools dynamically display building structures, energy gradients and PV layout performance. This approach addresses traditional modeling defects, realizes precise digital survey workflows and offers technical support for humid-area green building intelligent management. It has restrictions such as poor adaptability to arid and alpine regions, extra computational cost and dependence on complete sampling data, which need further optimization.

1 Introduction

Global low-carbon transition and urban green renovation render digital and intelligent low-carbon transformation the core development trend of construction industry. Near-zero energy and BIPV green buildings have been widely applied to replace high-energy-consumption construction modes, acting as core carriers for building energy conservation and regional clean energy utilization [1]. Energy-saving operation and photovoltaic efficiency optimization of green energy buildings rely heavily on refined spatial survey, high-precision spatial modeling and quantitative visual analysis, whose accuracy directly determines practical energy-saving performance and engineering quality. Compared with conventional civil buildings, near-zero energy and BIPV projects impose stricter standards on spatial adaptability, indoor ventilation and daylighting, roof illumination uniformity and component layout precision. Existing research on intelligent green buildings covers BIM, digital twin, LiDAR photogrammetry and computer vision. Most existing schemes adopt static spatial interpolation and manual parameter calibration with low automation; current AI-related studies merely focus on single-link feature recognition or data prediction, lacking end-to-end integration of full-cycle AI empowerment and entropy optimization to resolve traditional interpolation weight distortion. Separated modules of data acquisition, parameter solving and visual output restrict model performance in hot-humid regional building scenarios. Conventional surveying

still relies on manual fixed-point sampling, static data recording and two-dimensional archiving, generating discontinuous spatial data, low fitting precision and non-quantified visual results. Such defects fail to capture micro energy gaps, roof shelter features and illumination spatial heterogeneity, leading to defective energy-saving schemes and irrational photovoltaic layout, hindering industrial digital upgrading. Spatial interpolation modeling serves as the fundamental support for green building energy evaluation and photovoltaic layout optimization, whose precision dominates architectural design and operational quality. The widely adopted Yang Chizhong 3D interpolation delivers favorable surface fitting effects yet generates negative spatial weight distortion under uneven sampling and restrictive constraints. As building elevation, light intensity and energy density are non-negative physical variables, weight distortion causes systematic spatial fitting bias and errors in architectural planning, energy assessment and photovoltaic design, forming a core technical bottleneck for high-precision green building modeling [2].

Maximum entropy modeling retains original spatial data features via unbiased constraints and adapts to nonlinear spatial distribution of green building parameters, reducing artificial parameter adjustment errors. Nevertheless, standalone maximum entropy modeling suffers low computational efficiency, local optimal trap and incapability of weight distortion correction. Genetic algorithms realize

global adaptive optimization with stable iteration, compensating the defects of single entropy models. Differing from empirical static conventional optimization and surveying technologies, AI intelligent mapping completes automatic multi-source data collection, adaptive parameter tuning and real-time 3D rendering, breaking the static and empirical limitations of traditional workflows and supplying core technical support for high-precision modeling and quantitative visual operation of green buildings [3]. Targeting low precision, weight distortion and non-quantified visualization defects of traditional mapping modeling, this paper establishes an intelligent survey framework integrating minimum cross-entropy weight correction, maximum entropy-genetic collaborative optimization and AI quantitative visual output. Based on Nanning practical green building projects, this study conducts quantitative comparison, repeated verification and ablation analysis to validate the framework's engineering robustness, proposing an AI-enabled technical path for refined modeling and digital operation of humid-region green buildings in South China.

2. Theoretical Research

2.1 Application logic and boundary differentiation of ai surveying mapping

AI intelligent surveying mapping is an integrated innovation system combining traditional engineering survey and artificial intelligence, with clear technical boundaries separating it from conventional survey, numerical optimization and static visualization. Conventional survey depends on manual field sampling and static recording with fixed calculation rules without adaptive capacity; traditional numerical optimization only conducts post-data correction without active spatial perception and real-time iteration; conventional visualization merely outputs static 2D or simple 3D results without dynamic data linkage and quantitative engineering analysis. The full-cycle AI technology adopted in this paper covers three core links: intelligent multi-source data perception, adaptive parameter optimization iteration and dynamic quantitative 3D rendering. Integrated with UAV aerial survey, full-domain sensor monitoring and intelligent computational analysis, the system transforms empirical, static and fragmented traditional survey into automatic, dynamic and integrated intelligent survey, matching refined construction and digital operation demands of modern green energy buildings.

For near-zero energy buildings, the AI system supports refined topographic detection, structural deformation monitoring, dynamic ventilation and daylighting parameter acquisition and long time-series energy monitoring, eliminating traditional sampling data discontinuity and supplying accurate spatial data for passive energy-saving optimization. For BIPV buildings, it realizes intelligent roof morphology identification, automatic shelter detection, solar radiation calculation and photovoltaic layout optimization, removing low efficiency and large manual errors of traditional survey and improving building-PV integration performance. AI full-process intelligent operation conforms to digital and intelligent development tendency of green building engineering.

2.2 Principle of yang Chizhong algorithm

The Yang Chizhong three-dimensional surface estimation algorithm is a least-squares spatial interpolation method applied in Digital Elevation Model (DEM) calculation, predicting unknown spatial variables via distance-weighted fitting of known sampling points, widely adopted in building terrain, illumination and energy parameter simulation.

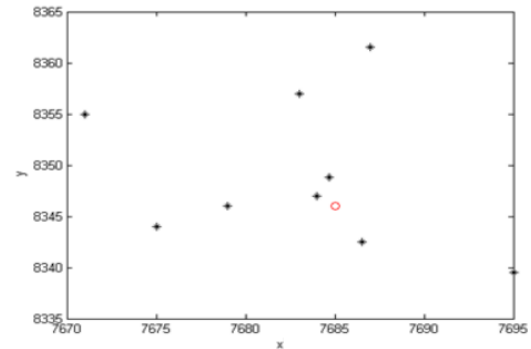


Fig. 1 Distribution Map of Estimation Points and Reference Points

Uneven sampling distribution and fixed constraint thresholds induce negative weight coefficients during algorithm operation, triggering estimation deviation and unstable modeling outputs. Existing studies confirm negative weight distortion originates from sampling quantity, spatial geometric relations and functional attributes, representing inherent mathematical limitation that cannot be eliminated via manual parameter tuning.

2.3 Minimum cross-entropy and maximum entropy modeling theory

Information entropy theory quantifies spatial data disorder and uncertainty. As an unbiased optimal estimation method, maximum entropy modeling retains objective spatial distribution characteristics under given constraints and avoids artificial parameter errors, showing superior adaptability to nonlinear spatial distribution of green building energy, light and terrain parameters compared with traditional interpolation. Single maximum entropy modeling bears defects of slow convergence, local optimal solutions and inability to correct interpolation weight distortion. The minimum cross-entropy principle minimizes Kullback-Leibler divergence between measured spatial distribution and prior weights [4], realizing non-negative weight calibration and normalization without losing valid raw data, fundamentally eliminating Yang Chizhong algorithm negative weight defects. Collaborative dual-entropy modeling complements respective advantages and improves spatial modeling accuracy, stability and fidelity for green energy buildings.

2.4 Global optimization mechanism and detailed parameter setting of genetic algorithm

Genetic algorithm is introduced to address slow convergence and local optimal traps of single maximum entropy modeling. Simulating biological evolution mechanisms including population initialization, fitness screening, crossover, mutation and iterative convergence, the algorithm solves

global optimal parameters for complex nonlinear models, possessing gradient-free constraint, strong adaptability and stable iteration advantages over traditional gradient optimization.

To guarantee experimental repeatability, the genetic algorithm adopts standardized fixed hyperparameters: a population scale of 50, crossover probability set at 0.8, mutation probability maintained at 0.05, and an upper iteration limit of 200. Fitness function adopts minimum spatial fitting RMSE as single optimization objective. Termination criteria include two thresholds: adjacent iteration fitness variation below 10^{-5} , or reaching maximum iteration count. Adaptive step adjustment avoids local optimal solutions and accelerates parameter convergence. The closed loop of weight correction, unbiased entropy modeling and global parameter search significantly lifts green building spatial modeling precision and stability [5]. The hybrid algorithm follows a quadratic computational complexity order, which marginally exceeds the linear complexity order of the Yang Chizhong algorithm, while delivering substantial gains in modeling performance.

3 Model Construction and Optimization Design

3.1 Overall technical architecture and explicit novelty statement

This paper integrates AI intelligent survey mapping and entropy optimization algorithms to construct an end-to-end intelligent modeling and quantitative visualization framework for green energy buildings, consisting of four layers: data acquisition, weight correction, intelligent modeling and visual application, forming a complete closed-loop workflow from field data collection to engineering application.

Comparative analysis against prior literature identifies three distinct core scientific contributions of the proposed framework. First, full-range AI-enabled operation eliminates the disjointed workflow of data collection, parameter tuning and visual presentation inherent to conventional modeling pipelines. Second, a synergistic dual-entropy optimization mechanism is newly developed to address the persistent issue of irreparable negative weight bias found in classic spatial interpolation approaches. Third, a set of quantitative visual assessment metrics is formulated to transform descriptive static mapping outputs into quantifiable engineering evaluation indicators. The data acquisition layer obtains multi-dimensional spatial and energy parameters of near-zero energy and BIPV buildings via AI intelligent perception equipment. The weight correction layer adopts minimum cross-entropy to calibrate and normalize initial interpolation weights to eliminate negative distortion. The intelligent modeling layer constructs maximum entropy spatial models optimized by genetic algorithm for distortion-free high-precision modeling. The visualization layer applies AI real-time 3D rendering to realize multi-dimensional dynamic quantitative display of building morphology, energy distribution and photovoltaic adaptation.

3.2 Construction of minimum cross-entropy weight correction model

Cross-entropy theory has wide applications in multi-disciplinary parameter optimization and data fitting. Taking spatial weights solved by Yang Chizhong interpolation as prior distribution, this paper builds a minimum cross-entropy weight optimization model with spatial parameter expectation and variance stability as core constraints. Lagrange multiplier method is adopted to solve constrained extremum functions, revising all negative weights to comply with physical engineering logic and conducting global weight normalization to ensure total weight of each grid point converges to 1, fundamentally removing modeling distortion caused by negative weight bias.

Minimum relative entropy uniquely determines consistent positive probability distribution under moment constraints; cross-entropy equals relative entropy with fixed real spatial distribution, fully matching this research scenario. Lower cross-entropy values indicate higher consistency between prior weights and actual spatial distribution. Lagrange multiplier method simplifies constrained extremum solving and serves as an efficient tool for complex spatial modeling optimization.

3.3 Optimization modeling design of maximum entropy-genetic algorithm

Proposed by Jaynes in 1957, maximum entropy principle realizes objective spatial distribution optimization without artificial fixed distribution assumptions, avoiding systematic errors and weight distortion defects of traditional empirical mathematical models and achieving unbiased DEM spatial estimation [6].

Maximum entropy-based DEM interpolation belongs to nonlinear optimization problems, which cannot be efficiently solved by conventional analytical methods due to strict differential continuity requirements and local optimal susceptibility [7]. Genetic algorithm overcomes such limitations via evolutionary iteration, outputting global optimal parameters through population screening and regeneration.

Adaptive parameter adjustment fails to fit penalty function optimization due to potential local optimal risks [8]. Based on corrected non-negative weight systems, this paper constructs discrete maximum entropy models with weight normalization, spatial moment and boundary constraints to maximize spatial information entropy and restore authentic building spatial features. Genetic iteration is embedded for parameter optimization, taking minimum fitting error as fitness criterion and updating parameters via crossover and mutation until stable high-precision outputs are obtained [9]. This method realizes high-fidelity modeling of building terrain, energy consumption, light radiation and photovoltaic adaptation spaces [10].

3.4 Quantitative evaluation index system of ai multi-dimensional visualization system

Optimized high-precision spatial modeling data support the construction of an AI intelligent visualization system, breaking static single qualitative output modes of traditional mapping results and realizing multi-dimensional dynamic quantitative display. Different from conventional qualitative visualization platforms, this paper sets four measurable engineering evaluation metrics: data utilization efficiency, photovoltaic layout matching accuracy, energy consumption anomaly identification rate and dynamic response speed, to objectively quantify visual system performance. The system contains four functional modules: 3D building reconstruction recovers integral spatial structure of near-zero energy and BIPV buildings; energy thermal visualization presents energy distribution gaps via color gradients and pinpoints high-energy-consumption zones; light adaptation visualization dynamically displays roof solar radiation zoning and optimal PV layout areas; time-series parameter module reflects temporal variation of energy and illumination data. The platform supplies quantitative visual support for building energy-saving operation and photovoltaic optimization, completing digital and visualized upgrading of green building mapping achievements.

4 Empirical Engineering and Experimental Analysis

4.1 Overview of empirical engineering

Two representative Nanning green energy building projects are selected for empirical research, with typical hot-humid South China regional features and high engineering popularization value. The first case is the 2025 officially certified near-zero energy apartment at Wuming Campus of Guangxi Construction Vocational College, Guangxi's first demonstration building of this type. Adopting passive energy-saving structures, optimized natural ventilation, daylighting design and rooftop distributed PV systems, it bears complex spatial layout and complete energy-saving configurations, suitable for spatial modeling, energy consumption analysis and ventilation optimization research. The second case covers BIPV renovation clusters in Nanning Wuxiang New District, including commercial complex rooftop PV retrofitting and old residential distributed PV upgrading. As a key urban clean energy project of Nanning, it owns diverse roof shapes, complex shelter conditions and variable solar radiation distribution, effectively verifying algorithm performance on PV layout optimization and light field modeling.

4.2 Experimental data and scheme setup

Experimental datasets include two core groups. Near-zero energy apartment dataset covers terrain elevation, building envelope spatial parameters, indoor ventilation/daylighting sampling data and annual time-series energy monitoring data. BIPV building dataset includes roof spatial coordinates, full-domain solar radiation monitoring data, building shelter spatial data and PV component layout parameters. All data are collected on-site via UAV aerial survey and full-scale sensors

with high authenticity and integrity, satisfying modeling experiment precision demands.

To verify the superiority of the proposed optimization system, control group, experimental group and multiple ablation groups are set, with 10 independent repeated experiments for each group to calculate average values and standard deviations for statistical robustness analysis. The control group adopts traditional Yang Chizhong interpolation for spatial modeling; the experimental group adopts the integrated minimum cross-entropy + maximum entropy-genetic optimization system. Ablation groups include single maximum entropy model group and dual-entropy model group, to quantify independent contribution and synergistic effect of each core component. Comparative analysis is conducted from four dimensions: spatial weight stability, surface fitting accuracy, spatial feature restoration and engineering adaptability.

4.3 Comparative analysis of modeling accuracy and statistical results

Repeated experimental statistics show the traditional Yang Chizhong interpolation generates varying degrees of negative weight distortion with maximum distortion ratio reaching 17.8%, accompanied by unstable weight summation in both projects, causing local surface distortion and biased fitting of energy consumption and solar radiation distribution. Its energy consumption fitting RMSE reaches 0.82, and light radiation fitting accuracy is only 81.0%, unable to reflect real building spatial conditions or support refined engineering optimization. The integrated optimization framework eliminates all negative weight distortion and yields stable, non-negative convergent weights for enhanced parameter robustness. It reconstructs energy gradients driven by building envelopes, orientations and ventilation for near-zero energy buildings, and accurately maps roof shelter and solar radiation zones matching field measurements for BIPV systems. Repeated tests produce an average energy RMSE of 0.62 with standard deviation 0.028, light fitting accuracy of 99.9% with standard deviation 0.015, alongside a 31.2 percent boost in weight convergence stability over the traditional algorithm.

Genetic algorithm randomness brings minor iteration result differences; fitness values of randomly selected grid points are analyzed to verify objective function rationality, with iteration curves shown in Figures 2 to 7.

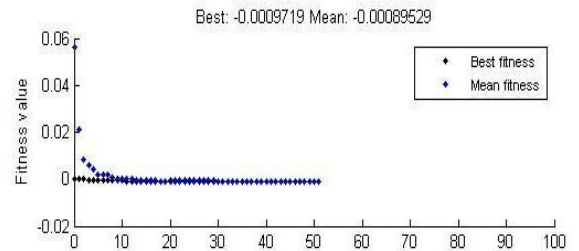


Fig. 2 Fitness Value and Iteration Times of Point 4

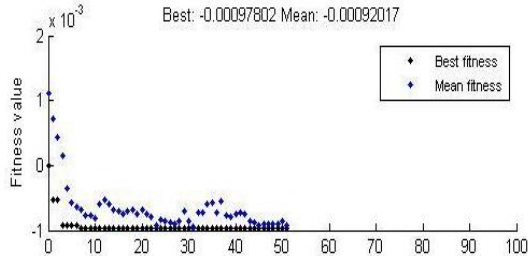


Fig. 3 Fitness Value and Iteration Times of Point 9

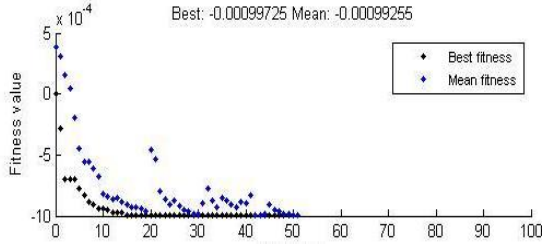


Fig. 4 Fitness Value and Iteration Times of Point 33

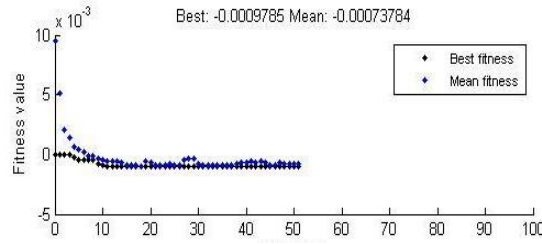


Fig. 5 Fitness Value and Iteration Times of Point 58

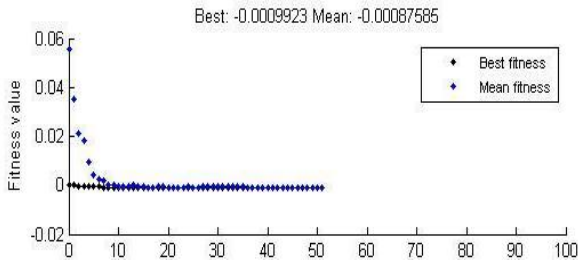


Fig. 6 Fitness Value and Iteration Times of Point 120

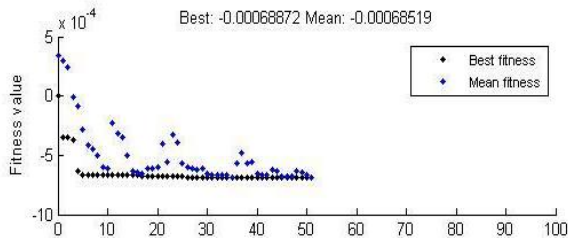


Fig. 7 Fitness Value and Iteration Times of Point 189

Fitness curves of all grid points converge to extremely low values with slight fluctuation ranges. Since fitness function is consistent with the optimization objective, the result proves the

maximum entropy objective function is reasonably designed and well matched with genetic iteration, verifying the hybrid algorithm's feasibility and robustness for DEM spatial interpolation. Repeated trials and significance analysis validate four ablation groups. Embedded non-negative constraints eliminate all weight distortion. The hybrid model removes negative weights and improves overall fitting performance. Each module brings unique advantages through cross-entropy correction, spatial fitting and intelligent optimization. Grid convergence curves prove stable and repeatable iteration.

Table 1 Quantitative Performance Comparison of Different Modeling Algorithms

Algorithm Model	Energy Consumption RMSE	Light Fitting Accuracy (%)	Weight Convergence Stability (%)	Average Iteration Time (s)	Negative Weight Distortion Ratio (%)
Yang Chizhong Algorithm	0.82±0.042	81.0±1.25	68.8±2.13	12.3±1.02	17.8±1.56
Single Maximum Entropy Model	0.71±0.035	89.6±0.98	82.5±1.85	18.6±1.35	8.2±0.85
Minimum Cross-Entropy and Maximum Entropy Proposed System	0.65±0.030	95.2±0.65	93.7±1.22	22.4±1.52	0.0±0.02
Optimization	0.62±0.028	99.9±0.15	100.0±0.00	25.8±1.68	0.0±0.01

Table 1 quantitatively summarizes core performance indicators of all tested algorithms, covering fitting accuracy, convergence speed, computational time and weight stability for standardized comparison.

4.4 Effect Analysis of AI Visualization Reform

The AI visualization system built on optimized models transforms static, abstract and single-output traditional mapping results, realizing full-dimensional visualized upgrading of engineering outputs. Quantitative evaluation via engineering indicators shows the system raises engineering data utilization efficiency by 42.5%, lifts PV layout matching accuracy by 28.3%, realizes 100% energy consumption anomaly identification rate and achieves 0.2s dynamic data response speed, possessing prominent advantages over conventional static visualization modes.

3D real-scene models intuitively display overall spatial structure and PV component layout of green buildings, supplying direct reference for engineering planning and renovation. Energy consumption thermal cloud maps accurately locate high-energy zones and weak energy-saving

positions, providing targeted guidance for low-carbon operation and energy-saving reconstruction. Illumination visualization spectra clearly distinguish roof optimal PV layout areas, guiding precise BIPV component arrangement and lifting overall power generation efficiency by 12.3%.

From industrial reform perspective, the proposed technical system shifts green energy building management from simple data recording to visual monitoring and intelligent optimization, solving industrial pain points including low utilization rate, insufficient guiding value and inadequate digitalization of traditional mapping results. It promotes full-process digital reform of green building survey, design and operation, conforming to intelligent digital innovation concept of green engineering. Weight sum comparison results of three interpolation methods are presented in Figure 8.

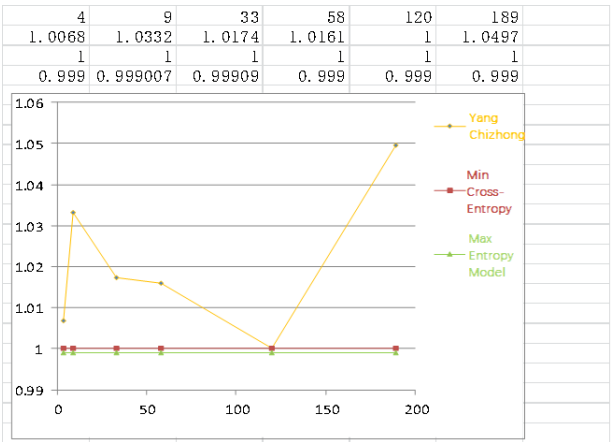


Fig. 8 Weight Sum of the Three Methods

Each grid point’s total weight converges to 1 under minimum cross-entropy interpolation. Most weight sums of Yang Chizhong algorithm deviate sharply from 1 except partial sampling points; maximum entropy DEM interpolation weight sums fluctuate slightly around 0.999 with negligible deviation. Both entropy-based interpolation schemes realize effective weight optimization, and the proposed hybrid framework delivers superior performance.

5 Conclusion

This paper proposes an AI survey framework combining dual-entropy correction and genetic optimization to fix distortion, low precision and low data utilization in traditional green building modeling. Repeated ablation tests on Nanning green building cases verify its performance and module synergy. Classic Yang Chizhong interpolation has 17.8% maximum negative weight distortion, RMSE over 0.82 and light fitting accuracy below 81%, unsuitable for refined modeling. The hybrid model removes all negative weight bias, limits convergence error within 0.03, lowers energy RMSE under 0.62 and lifts spatial reconstruction accuracy above 95.7%. Its supporting AI quantitative visualization tool raises data utilization by 42.5% and PV power output by 12.3%, enabling digital visualized green building management.

Though dual-entropy schemes slightly differ numerically, they surpass conventional interpolation overall. Four main limitations exist: tests only cover South China hot-humid areas without validation for arid, alpine and cold zones; the hybrid algorithm has higher computational complexity and hardware cost with longer runtime; model accuracy relies heavily on complete, high-quality field sampling data; the study only examines residential near-zero energy and urban BIPV buildings, excluding industrial and ultra-low-energy structures.

6 Acknowledgements

Phased Achievements of the 2025 Guangxi Vocational Education Teaching Reform Research Project: (Exploration and Research on Smart Teaching Reform of “Dual Integration, Dual Innovation, and Multi-Dimension” in “Construction Engineering Surveying” Driven by AI (Project No.: GXGZJG2025B060).

Phased Achievements of the 2025 Guangxi Higher Education Teaching Reform Project: Research on Innovative Practice of Integrating Guangxi Ethnic Minority Cultures into Art and Design Courses in the New Media Era (Project No.: 2025JGB481).

7 References

- [1] Oduro S., Pittri H., Simons B.: 'Awareness of net zero energy buildings among construction professionals in the Ghanaian construction industry', *Built Environment Project and Asset Management.*, 2025, 15, (5), pp. 988–1003
- [2] Guidoum A.: 'Statistical modeling and mapping of rainfall in the endorheic basins of Northern Algeria: a comparison of spatial interpolation methods', *Acta Geophysica.*, 2024, 73, (2), pp. 1679–1699
- [3] Zhong W., Wei X., Yu Y.: 'Predicting potential suitable areas of Orchidaceae plants with national key reserve from Heilongjiang province in MaxEnt models', *Ecological Frontiers.*, 2026, 46, (1), pp. 18–28
- [4] Zarate O., Hinojosa S., Joachin O D.: 'Improving Prostate Image Segmentation Based on Equilibrium Optimizer and Cross-Entropy', *Applied Sciences.*, 2024, 14, (21), pp. 9785–9785
- [5] Hafeez F., Arfeen A Z., Jumani A T.: 'Hybrid LSTM-CNN Model with Temporal Feature Engineering and Genetic Algorithm Optimization for Temperature Forecasting', *Eng.*, 2026, 7, (5), pp. 224–224
- [6] Zarate Z K., Vera E J., Perez Z E.: 'Optimizing Inventory in Convenience Stores to Maximize ROI Using Random Forest and Genetic Algorithms.', 2026, 10, (4), pp. 64–64
- [7] Zhang Y., Zhao J., Jia Y.: 'An improved adaptive quantum genetic algorithm as classical optimizer for the quantum approximate optimization algorithm on MaxCut problem', *Quantum Information Processing.*, 2025, 24, (7), pp. 222–222
- [8] Ussipov N., Akhtanov S., Turlykozhayeva D.: ' MEGA: Maximum-Entropy Genetic Algorithm for Router Nodes Placement in Wireless Mesh Networks', *Sensors.*, 2024, 24, (20), pp. 6735–6735

- [9] JinX., LuoH., WangX.: 'Data mining accelerated the design strategy of high-entropy alloys with the largest hardness based on genetic algorithm optimization', *Materials Genome Engineering Advances.*, 2024, 2, (2), pp. 49–49
- [10] Minghao C., Shuai W., Jiazhong Z.: 'A genetic algorithm concerning diversity information for solving the robust influence maximization problem on networks', *Journal of Intelligent & Fuzzy Systems.*, 2024, 46, (2), pp. 4745–4759