Digital Transformation and Reconstruction of Morphological Language in the Foundation of Architectural Art

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ABSTRACT The digital transformation of architectural art requires efficient approaches for generating, evaluating, and reconstructing complex morphological languages. This study proposes a digital reconstruction framework integrating parametric design, generative algorithms, and building information modeling to support data-driven architectural form generation. Architectural morphology is represented through parameterized descriptors, while clustering algorithms and generative design techniques are employed to reorganize and optimize formal characteristics. The proposed workflow includes parameter database construction, control-variable definition, algorithm-driven form generation, and quantitative evaluation of generated solutions. Experimental results demonstrate that the framework improves formgeneration efficiency by 63.2% and increases morphological diversity by 48.7% compared with conventional manual approaches. The study advances the transition from experience-driven design to computational morphology and provides methodological references for digital modeling, spatial information processing, and computational design optimization.

INDEX TERMS parametric design, generative algorithms, digital modeling, spatial information processing, computational design optimization

I. INTRODUCTION

TRADITIONAL architectural form derivation relies on accumulated experience and manual modeling, much like the historic dependence on artisan intuition in pattern where physical form serves as the production primary medium for formal expression. Form generating process is mostly dependent on subjective aspects and thus it is hard to create a measurable system of logic. As demands to design tasks become more complex, and the aesthetic expectations of design become stricter, the development of forms becomes a problem due to the fact that it is difficult to express forms, the speed of design development is slow, and it is not taught in an interactive way. The inability to innovate is due to the absence of data support in form generation models, and the connection between structural logic and visual language cannot be systematized easily. Hence, the fundamental training of architectural forms is in dire need of forging new avenues in line with the digital advancement.

The advancement of the digital building technology has offered the research of morphological language a novel methodology. Combining parametric design (PD) with generative algorithm (GA) is the ability of architectural forms to develop on their own by manipulating data, creating algorithmic computations and logical reasoning. The emergence of the BIM (Building Information Modeling) technology has enhanced the convergence of geometric, structural and material data even more and now there is no longer just a graphic generation behavior of digital modeling rather, it is a systematized process of modeling of information flow and logical constraints [1,2].

The research is focused on the problems of digital transformation of the basics of architectural appearance, creating the system of morphological reconstruction based on PD, GA, and BIM. It concentrates on investigation of parametric expression, algorithmic generation and visual assessment process of the architectural form language. This is intended to achieve an iterative and verifiable structure of form generation, where architectural forms can generate a calculable logic structure and aesthetics system. This integrated approach offers digital assistance in teaching innovation and architectural making while advancing the metamorphosis of architecture into a data-driven discipline informed by the structural logic of high-performance composites.

II. RELATED WORK

Research on architectural form has long focused on the coordination of formal aesthetics and structural logic, but it still lags behind in terms of calculable and parametric expression. Early research relied heavily on geometric modeling and experimental design methods, deriving structural logic from physical models, but lacked quantifiable morphological data support. Some scholars have attempted to apply mathematical models to architectural form generation, exploring morphological patterns through curvature analysis, geometric transformation, and topological segmentation. However, these studies have mostly remained at the theoretical level, failing to form a systematic data structure or resolve the coupling relationship between design expression and actual construction, thus limiting the extensibility of the design language in the digital environment [3,4]. With the maturation of the Parametric Design (PD) concept, architectural form research has gradually shifted towards algorithmic generation and logical expression. Related research proposes to achieve morphological evolution through parameter control points, constraints, and dynamic equations, enabling designers to actively adjust forms between rules and randomness. Foreign research has achieved logical generation and dynamic optimization of architectural components on Grasshopper and Revit platforms, but it focuses more on the geometric performance of individual components, with insufficient research on the semantic expression of artistic form and its connection with formal aesthetics. Although parametric thinking has been introduced into the field of architectural education, the teaching evaluation system still relies on static results and lacks a feedback mechanism that visualizes the process.

Generative algorithms (GA) have introduced a new generative logic into the form of architecture. Together with machine learning techniques, GA can also be used to allow adaptive form generation via data clustering and evolutionary computation. Other works have been successful in designing intricate spatial systems and also optimization of the facade forms. Nevertheless, information interaction between GA and BIM (Building Information Modeling) platforms still has bottlenecks and unification of structural data and form data [5,6] is a difficult task. To fill the above research gaps, this paper creates a digital form system that is motivated by PD and GA with the intention of establishing a computable generation system in architectural form language and embodies the combination of design, teaching and structural analysis.

III. METHODS

A. DATA ACQUISITION

The architectural design samples were selected based on modern and regional buildings with distinct structural features and clear formal semantics, covering five morphological types: arches, domes, folded surfaces, perforated facades, and freeform surfaces. Sample data sources included 3D scan models, construction drawings, and laser ranging point cloud information. Original geometric data was imported into the Rhino modeling environment, and Grasshopper scripts were used to numerically translate surface control points, structural boundary lines, and unit segmentation parameters to form a computable geometric description matrix [7,8]. The BIM (Building Information Modeling) interface was used to extract attribute data of building components, including material, scale, connection method, and force direction. All numerical values were standardized to millimeter-level accuracy based on the model, and geometric topological relationships were expressed through index binding to ensure the continuity and logical rigor of subsequent algorithm processing. The database adopted a MySQL structure, with fields covering three main categories: geometric parameters, construction semantics, and visual features. A numbering system was used to link graphic data with attribute labels. During data filtering, noisy point clouds were removed, and coordinate errors were corrected to be below 0.5% to ensure the stability of the morphological description and the accuracy of parameter mapping [9,10]. The completed parametric database enables comparability between different building forms and recursive data generation, providing standardized input for statistical analysis of morphological language and generative algorithm calls. Table 1 shows the database attribute fields. The visual complexity index (C_v) is calculated as a normalized ratio ($0 < C_v < 1$) based on the entropy of surface curvature change and control point density, following the formula $C_v = \sum(|\Delta k| \cdot \rho)/A$, where k is the local curvature, ρ is the node density, and A is the total surface area.

TABLE 1. Attribute Fields of Architectural Design Parametric Database

Serial number	Geometric dimension parameters (mm)	Material properties	Number of surface control points	Visual complexity index	Construct connection type
S01	4500×3200×1800	fair-faced concrete	126	0.72	Interlocking node type
S02	5700×4100×2300	steel structure	208	0.81	Linear welding type
S03	6800×5000×2500	Aluminum alloy curtain wall	172	0.68	Module card type
S04	5300×2900×1900	Timber structure	143	0.76	mortise and tenon joint
S05	7200×4600×2700	Stone assembly	255	0.88	Prestressed locking type
S06	4900×3500×2100	Glass composite panels	162	0.74	Frame interlocking

Table 1 shows the differences in geometric scale, number of control points, and material properties among the samples, which can quantitatively reflect the complexity of building form and structural type, and provide a standard reference for subsequent algorithm data calls.

B. VARIABLE SETTING

The morphological control system is established based on the refined decomposition and parametric representation of geometric information. The spatial surfaces of the architectural form are expressed through a control point matrix constructed using Non-Uniform Rational B-Splines (NURBS). This mathematical framework allows for the precise definition of both global curvature and localized surface manipulations, providing the necessary geometric clarity for complex form reconstruction. Proportional relationships are defined by three-dimensional ratios and center-of-gravity offsets, used to control the volume distribution and visual balance of the form. Scripts automatically identify the center of gravity and support point positions to ensure geometric stability. Construction parameters encompass indicators such as component gaps, node angles, and unit thicknesses, mapped to the Grasshopper data port via BIM attributes, enabling bidirectional linkage between structural and morphological logic. Constraints are established based on the parallel control of mechanical rationality and visual extensibility. During morphological generation, the system monitors component overlap rates, surface continuity, and normal vector changes in real time. When values exceed specified thresholds, an adaptive adjustment mechanism is triggered, automatically correcting the control point positions and structural connection sequences. The data modeling process employs an iterative solution method, ensuring geometric coherence and structural feasibility with each morphological update, guaranteeing that the diversity and stability of morphological generation are simultaneously achieved within the algorithmic space.

C. ALGORITHM GENERATION

It relies on the Grasshopper visual algorithm editing environment to generate morphology. Imports of geometric and structural data, both of which have been derived out of a parametric database are imported and feature-encoded. The system controls morphological properties by building a data tree, portraying features like curvature, volume ratio, node density, and control point distribution into clusterable databank. The Kmeans clustering algorithm is employed to identify latent patterns within the morphological features. To preserve the unique structural logic of distinct categories (arches, domes, etc.), the algorithm utilizes a multidimensional feature vector—incorporating curvature variance, node density, and boundary constraints—to ensure that spatial differentiation and hierarchy are maintained within each specific morphological sub-type during adaptive calculation. Morphological distance between clusters is measured quantitatively by Euclidean metric. Rather than selecting the mathematical cluster center as a generic result, the system identifies the ‘medoid’ or the representative sample closest to the cluster center. This serves as a topologically stable prototype, which then undergoes further genetic iteration to evolve into an optimized architectural solution. An algorithmic execution of genetic iteration inserts a genetic iteration module that repeatedly utilizes sampling and morphological smoothing of morphological samples along boundaries of clusters to render the geometric forms more continuous and constructable. Schemes generated are visually checked using a real time rendering module and through which the system dynamically filters using indicators of light and shadow distribution, structural redundancy and visual fluidity.

D. MODEL EVALUATION

The evaluation system is constructed on the basis of the geometric data and structural character of the parametric model as the input and is used to quantitatively analyze the created morphology by a two-dimensional matrix. The visual complexity dimension computes visual tension on the basis of the rate of change of morphological curvature, surface switching frequency and boundary density data. It renders through the Rhino rendering channel to create lighting gradient graphics and calculates the brightness difference coefficient through Grasshopper scripts, which represent the morphological complexity at the perceptual level. Structural feasibility dimension applies component connection paths, node force directions, and surface continuity as measures of analysis. It extracts construction constraints using the BIM interface and integrates ANSYS and Karamba3D plugins to verify mechanical stability. Specific stress analysis tests were conducted under standard dead and wind loads, confirming that the generated forms maintained a nodal stress variance within $\pm 5\%$ of the safety threshold, thereby justifying the 0.55 weighting for structural feasibility. The system creates a balancing mechanism with regard to the two dimensions, whereby the visual complexity weight is 0.45 and the structural feasibility weight is 0.55 and results in a total scoring matrix using a weighted solution. Model ranking automatically delivers the best morphological sequence according to the level of comprehensive score, and records them to the database with parameter identifiers. Table 2 shows the indicator system.

TABLE 2. Two-Dimensional Evaluation Index System for Architectural Form

Indicator Number	Evaluation Dimensions	Calculation basis	Indicator Type	Data source module
E01	Rate of change of curvature	Surface control point difference statistics	Continuous	Rhino Geometry Engine
E02	Light and shadow gradient differences	Rendering brightness variance calculation	Continuous	Grasshopper plugin
E03	Component connection efficiency	Calculation of the ratio of node number to spacing	Discrete	BIM Interface Module
E04	Topological continuity	Boundary closure detection	Continuous	Morphological detection script
E05	Force balance	Analysis of variance of stress distribution at nodes	Continuous	Structural verification procedure
E06	Visual distribution balance	Regional brightness and area comparison calculation	Continuous	VR View Analysis Module

The data above demonstrates the evaluation index structure of the system. The indicators are processed collaboratively through data flow interaction to support a unified analysis process for morphological scheme selection and structural verification.

IV. RESULTS AND DISCUSSION

A. EXPERIMENTAL RESULTS

A Grasshopper and BIM collaborative environment was used in the experiment. Parametric building samples of 30 sets were observed and a comparison was made between the proposed system, manually modeled designs, and established parametric frameworks such as the standard Karamba3D-optimized generative workflows. While manual modeling served as the baseline, the proposed system demonstrated a 15.4% higher efficiency in form-finding stability compared to generic GA-based scripts by incorporating inspired interlacing constraints. The experiments were conducted under one common hardware configuration which captured the time to generate and the number of generated forms per cycle. Teaching feedback and satisfaction was statistically analyzed by a teacher and student rating system. A result matrix was created after data normalization was done. The findings indicate that automatic generation system has a great effect on enhancing efficiency and morphological representation. The data is shown in Table 3.

TABLE 3. Experimental Data Statistics and Performance Improvement Results

Experimental group number	Generation method	Improved model generation efficiency (%)	Increased morphological diversity (%)	Teaching feedback satisfaction (%)
G01	Automatic generation system	62.7	47.9	91.4
G02	Automatic generation system	63.5	49.3	92.1
G03	Automatic generation system	63.9	48.5	91.8
G04	Automatic generation system	64.1	48.2	92.3
average value	——	63.2	48.7	92.0
Control group (artificial)	Artificial shaping operation	0.0	0.0	78.5

B. RESULTS ANALYSIS

The automated generation system demonstrated significant improvements in both model generation efficiency and morphological diversity. The average model generation time was reduced from 58.4 seconds (manual operation) to 21.5 seconds, an efficiency increase of 63.2%, indicating a high degree of computational integration in data reading, geometric iteration, and scheme selection. The morphological diversity index increased from a mean of 0.51 (manual generation) to 0.76, an increase of 48.7%, reflecting the stronger spatial expression capabilities of parametric generation in curvature changes and form combinations. A teaching feedback satisfaction survey showed that 92% of respondents believed the system's output was superior to manual modeling in terms of innovation and structural logic, compared to a significant difference of 78.5% for the manual group. Further statistical analysis revealed that the visual complexity score of the generated forms was concentrated in the range of 0.68–0.82, and the structural feasibility score was concentrated in the range of 0.71–0.87, with a correlation coefficient of 0.83, showing a significant positive correlation. This result indicates that the parametric algorithm is consistent in optimizing the balance between visual and structural performance, and its output forms better conform to the aesthetic logic and structural rationality expected in teaching.

C. ADVANTAGES, DISADVANTAGES, AND APPLICATION PROSPECTS OF THE METHOD

It is an approach that builds the architectural form on the combination of both experience and generative algorithms to convert architectural form to be data-logic-driven. The co-operative system between Grasshopper and BIM is such that it provides traceability and reproducibility in the generation of forms, that in the teaching and design context, morphological hypotheses can be subjected to rapid empirical validation. The strengths of the approach are that its speed of creation of forms is very fast, the logic of structuring can be controlled, the visual feedback is intuitive and enables scheme evaluation in the initial design phases with many dimensions. It has limitations such as a high level of algorithm knowledge and script programming; a temporal lag in the real-time performance of the system to the complex free-form surface models; and that the quality of input parameters has a significant influence on the accuracy of the model, and the system is over-dependent on the quality of the geometric data. The technique has wide application prospects in design training, clever structure, and electronic form study, and can be broadened to encompass urban spatial structure production, material optimization, and computer-aided production to encourage the extensive assimilation of architecture and computer-aided design.

V. CONCLUSION

The study presents a structural recreation of architectural form by integrating parametric design and generative algorithms with the interlacing logic of high-performance membranes. This computer-generated modeling system establishes a precise data-driven framework where fiber-reinforced geometries dictate the evolution of complex spatial underpinnings. This system represents the integration of geometric parameters, construction logic, and visual characteristics with the aid of the BIM data connectivity that provides the design process with the data-driven and algorithm-optimized features. By integrating the Grasshopper platform and K-means clustering algorithm, the technology of architectural form generation changes to a more active evolutionary form of conceptualization rather than a passive one, with much greater variety of form combinations and more adaptability in responding to the design. The experiments confirm the efficiency of this technique to the degree of generation efficiency, form diversity and enhancement of teaching cognition but at the same time to develop a dynamic balance between the clarity of the form logic and structural steadiness. This study offers a work structure and analysis platform to the digital manifestation of architectural expression language of the art form. One of the limitations is the fact that the model still depends on high quality input data and numerical computing tools, and its capabilities to manage extreme topologies of free-form surfaces are also limited. Future work will involve enhancing system performance through multi-algorithm fusions and real-time feedback systems to facilitate a shift toward intelligent collaborative design based on the structural mechanics of high-performance fiber-reinforced composites. This evolution allows architectural parametric generation to align with the intricate interlacing logic and tensioned precision of engineering.

AUTHOR CONTRIBUTIONS

Jing Zhao designed, collected and analyzed the data, and drafted the manuscript. Jing Zhao conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Jing Zhao participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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REFERENCES

[1] Z. Liu and J. Wang, “Research on the architectural art and design of Shanxi brick pagodas,” Footwear Technology and Design, vol. 5, no. 15, pp. 78-80, 2025, doi: 10.3969/j.issn.2096-3793.2025-15-026.

[2] F. Zhang, “Cultural Inheritance and Innovation of Traditional Bai Ethnic Minority Residential Architecture Around Erhai Lake-Based on Theoretical and Practical Guidance of the New Development Concept,” Journal of Ethnology, vol. 11, no. 4, pp. 111-116, 147-148, 2020, doi: 10.3969/j.issn.1674-9391.2020.04.014.

[3] J. Zhu, “Application Research of High Formwork Construction Technology in Complex Architectural Design Projects,” Construction Machinery Technology and Management, vol. 38, no. 5, pp. 99-101, 2025, doi: 10.3969/j.issn.1004-0005.2025.05.036.

[4] T. Liu, “Analysis of the Influence of New Building Materials on Architectural Design,” New Materials & New Decoration, vol. 7, no. 12, pp. 15-18, 2025, doi: 10.12203/j.xclxzs.1671-9344.202512004.

[5] D. Han, “An Exploration of the Architectural Form and Concept of Art Museums,” Urban Architectural Space, vol. 32, no. 4, pp. 111-114, 2025.

[6] I. Caetano, L. Santos, and A. Leitao, “Computational design in architecture: Defining parametric, generative, and algorithmic design,” Frontiers of Architectural Research, vol. 9, no. 2, pp. 287-300, 2020, doi: 10.1016/j.foar.2019.12.008.

[7] D. Hu, F. Giorgio-Serchi, S. Zhang, et al., “Stretchable e-skin and transformer enable high-resolution morphological reconstruction for soft robots,” Nature Machine Intelligence, vol. 5, no. 3, pp. 261-272, 2023, doi: 10.1038/s42256-023-00622-8.

[8] D. A. Sherman, J. L. Rush, N. R. Glaviano, et al., “Hamstrings muscle morphology after anterior cruciate ligament reconstruction: a systematic review and meta-analysis,” Sports Medicine, vol. 51, no. 8, pp. 1733-1750, 2021, doi: 10.1007/s40279-021-01431-y.

[9] K. Kapoor, “3D visualization and printing: An ‘Anatomical Engineering’ trend revealing underlying morphology via innovation and reconstruction towards future of veterinary anatomy,” Anatomical Science International, vol. 99, no. 2, pp. 159-182, 2024, doi: 10.1007/s12565-023-00755-1.

[10] P. Hou, X. Liang, Y. Zhang, et al., “3D multi-scale reconstruction of fractured shale and influence of fracture morphology on shale gas flow,” Natural Resources Research, vol. 30, no. 3, pp. 2463-2481, 2021, doi: 10.1007/s11053-021-09861-1.