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Research Paper

A Review Analysis of Performative Computational Architecture (PCA) Process with Emphasis on Performance Goals and Physical Factors*

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ABSTRACT

Performative Computational Architecture (PCA) is an intelligent approach to the design process based on performance criteria, which has generated considerable conceptual confusion among some students, designers, and researchers. Furthermore, this concept entails various factors depending on the design subject, necessitating examination, prioritization, and analysis. This study aims to conduct a review of Performative Computational Architecture based on evolutionary and swarm computation methods and elucidate its performance and architectural factors. The research method employed is a comprehensive quantitative-qualitative approach, analyzing content from the literature on the subject of Performative Computational Architecture. The statistical population of this research includes studies conducted from approximately 2002 to 2021, with purposive sampling and snowball sampling techniques utilized. Data analysis was conducted through descriptive analysis and correlation and Shannon tests on the topics and factors examined. The findings indicate that research in the field of Performative Computational Architecture has been conducted on three main subjects: skin, form, and building layout. Among these, shading, window dimensions, window placement, and window-to-wall ratio emerge as the most significant factors in skin formation and facade design. The overall form, floor height, and the number of buildings are highlighted as key factors in form generation for building design, while spatial location, adjacency matrix, and grid matrix are identified as crucial factors in generating building layout design. Based on the findings, it can be concluded that Performative Computational Architecture, as a performance-based design approach, embodies three shared design concepts: generative design, algorithmic design, and parametric design, with a focus on performance evaluation and optimization. Additionally, form-finding factors exhibit diverse degrees of importance based on the triadic subjects, among which spatial location and adjacency matrix in building layout configuration, shading in skin formation, and overall building shape in form emerge as key form-finding factors.

Keywords: Performative Computational Architecture, Performance-based Design, Computational Optimization, Swarm Intelligence, Architectural and Performance Factors.

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1. INTRODUCTION

The architectural design process can be classified as a complex and ill-defined problem, lacking clear pathways for solutions and well-defined criteria for analyzing and evaluating outcomes (Hassan et al. 2022). This complexity arises from parameters that are not easily measurable (Du et al. 2020; Wei et al. 2014). One of the primary reasons for the complexity of architectural design is that multiple objectives significantly influence the overall performance of the intended design (Shi and Yang 2013). Often, these objectives conflict with each other. Additionally, each design is based on a set of problems, objectives, construction plans, constraints, client expectations, and the side effects of the surrounding built environment. Therefore, the design process is a multi-objective problem (Magnier and Haghighat 2010) and is iterative (Cobb et al. 2003), requiring increasing awareness to achieve desired results (Ekici et al. 2019). This has led to a heightened focus on the use of computational systems in design (Du et al. 2020), as in these systems, design is amendable and revisable from the outset of the process (Sonta et al. 2021). With technological advancements and the availability of hardware and software, the use of computers in architectural design, particularly in complex design computations (Barbieri and Muzzupappa 2022), has increased both in research centers and industries, and this trend continues. Currently, the use of computers in parametric design (Wu et al. 2022), generative design (Gan 2022), and algorithmic design (Bakhshi et al. 2022) is increasingly expanding in the architectural design process and interdisciplinary development.

One of the approaches to using computers in design is the generative design approach, which was introduced in the late 1970s by Mitchell (Mitchell 1975). This research introduced generative design systems as tools capable of generating potential solutions to a specific problem. In the following two decades, literature rarely addressed generative design. At the beginning of the twenty-first century, Fischer and Herr (Fischer and Herr 2001) defined generative design as an approach in which the designer does not directly engage with materials and products during the design process but rather through a generative system. According to Caldas (Caldas 2008), this system is evolution-based and searches the design space for solutions that meet functional requirements. Generative design employs various structures. One intelligent structure that has garnered significant attention from designers today is the performance-based design approach (Ekici et al. 2019). This approach, as a necessary method for achieving transformed objectives, can predict building functions based on design variables (Chegari et al. 2021). Performance-based design explores design options with better performance by making changes in design factors and observing results (Wei et al. 2014). Kolarevic (Kolarevic 2003) emphasized the importance of performance-based design as a guiding design principle and categorized its various methods. Among the numerous possible methods, this research focuses on a specific framework of performance-based design known as "Performative Computational Architecture."

Performative Computational Architecture, due to the combination of two subjects: generative architectural design and computational optimization, is characterized by considerable conceptual ambiguity among some students, designers, and researchers (Du et al. 2020), with this ambiguity more pronounced in domestic research. Additionally, Performative Computational Architecture encompasses various and diverse factors depending on the design subject, requiring organization and prioritization (Ekici et al. 2019). Therefore, the lack of a comprehensive review in the field of Performative Computational Architecture, its related design topics, and its performance and architectural factors, especially in domestic research, is felt. Based on the above, this study aims to conduct a comprehensive review of Performative Computational Architecture and examine the holistic architectural and performance factors. Thus, the main question of this research is how the structure of Performative Computational Architecture is defined and based on what topics and what architectural and performance factors? Additionally, this question is raised as to how each of the factors of this concept is utilized in which design topic and what importance it holds in that topic?

2. BACKGROUND OF THE RESEARCH

The concept of Performative Computational Architecture was first introduced by Sariyildiz (2012), but its background traces back to three concepts: Parametric Design, Algorithmic Design, and Generative Design. These concepts share both similarities and differences. Generative Design can be considered the closest concept to Performative Computational Architecture. The Cambridge Dictionary defines "generative" as the capacity to produce or create something. Some authors introduce generative design as a design process using evolutionary techniques to generate solutions (Fischer and Herr 2001; Frazer et al. 2002; Zhang and Xu 2018), while others do not limit generative design to evolutionary processes; rather, they consider it as an approach based on algorithmic or rule-based processes that produce diverse and potentially complex solutions (Bernal et al. 2015; Humppi and Osterlund 2016). Additionally, several authors consider approaches such as algorithmic generation, cellular automata, evolutionary methods, L-systems, shape grammars, selforganization, agent-based models, and swarm systems as part of the generative design approach (Abdelmohsen 2013).

On the other hand, the concept of Parametric Design is often mistaken for generative design in many cases. The Oxford Dictionary defines "parameter" as a numerical factor or measurable factor that defines a system or determines its performance conditions and constraints, and the term "parametric" is described as "related to a parameter" or "the parameters themselves" (Caetano et al. 2020). According to the literature, parametric design is defined as a design process based on algorithmic thinking that uses parameters and rules to define design conditions (Marin et al. 2015; Yu and Gero 2015). Additionally, this concept is related to the Building Information Modeling (BIM) paradigm, which establishes dependencies between various design elements. In other words, parametric design is a method that describes a design symbolically based on parameters (Zboinska 2015). For example, instead of designing walls using specific positions, lengths, heights, and thicknesses, these characteristics are replaced by symbolic parameters with specific domains (Janssen and Stouffs 2015). Examples of parametric design architecture include the Hangzhou Olympic Sports Center by NBBJ Architects and the Qatar Rail Project by UN Studio, where design studios developed parametric programs enabling them to create diverse buildings by altering design parameters (Caetano et al. 2020).

Another term, Algorithmic Design, overlaps significantly with parametric design and generative design in the literature (Bukhari 2011), confusing in defining algorithmic design. As the name suggests, Algorithmic Design is a design process based on algorithms (Zboinska 2015). According to the Cambridge Dictionary, an algorithm is a set of instructions or mathematical rules that help calculate the solution to a problem. Therefore, distinguishing algorithmic design from generative design is challenging (Bukhari 2011). Research by Caetano et al. (2020) considers Algorithmic Design as a design pattern that uses algorithms to generate models, somewhat akin to generative design. According to this definition, Algorithmic Design is a subset of generative design, focusing on algorithmic development with fewer new results generated for predefined designs (Caetano et al. 2020).

Considering these two perspectives, if generative design is distinguished from other terms like parametric design, it can be defined as a design pattern that uses algorithmic descriptions independently of parametric design. In generative design approaches, after initiating the production process, the system executes encoded instructions until the termination criterion is met. Therefore, generative design methods can produce complex outputs even from simple algorithmic descriptions. Performance-based Generative Design Systems (PGDS) are good examples of the application of generative design. In these systems, a designer defines a performance objective and a search algorithm finds design solutions that optimize the desired objective. Performative Computational Architecture, as one of the performance-based approaches, was proposed by Sariyildiz (2012) at Delft University to enhance the design process. The main goal of Performative Computational Architecture is to find the best geometry that achieves various performance goals in the conceptual design phase through automation. The Performative Computational Architecture framework consists of three stages: Form Generation, Performance Evaluation, and Optimization (Ekici et al. 2019) (Fig. 1).

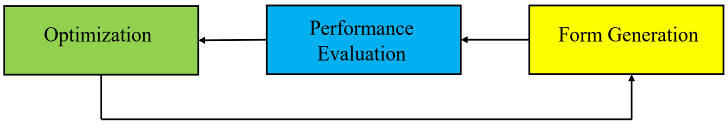

Fig. 1. Performative Computational Architecture (PCA) Framework Cycle
(Sariyildiz 2012)

Additionally, Kiss and Szalay (2020) present a similar structure under the title of the Life Cycle Assessment (LCA) framework in five sections. The main objective of the research by Kiss and Szalay (2020) is to create a framework for automatic optimization of the life cycle in a project (Fig. 2). In this model, the assessment section is introduced in the form of two parts: calculations and result evaluation. Additionally, a section called input data is also introduced as a pre-production process.

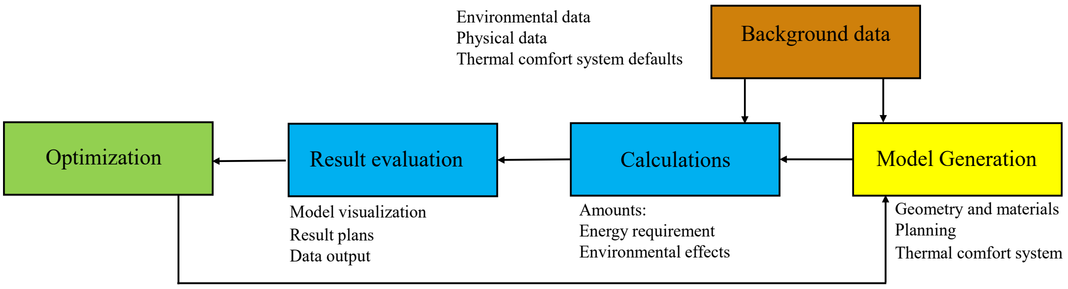

Fig. 2. Building Life Cycle Assessment (LCA) Framework
(Kiss and Szalay 2020)

The report by Autodesk University in 2017 (Nagy et al. 2018), titled "Generative Design in a Larger Context," belongs to a larger ecosystem that is completed with two processes before and after generative design. It integrates with the design process through the use of creative search algorithms (Fig. 3).

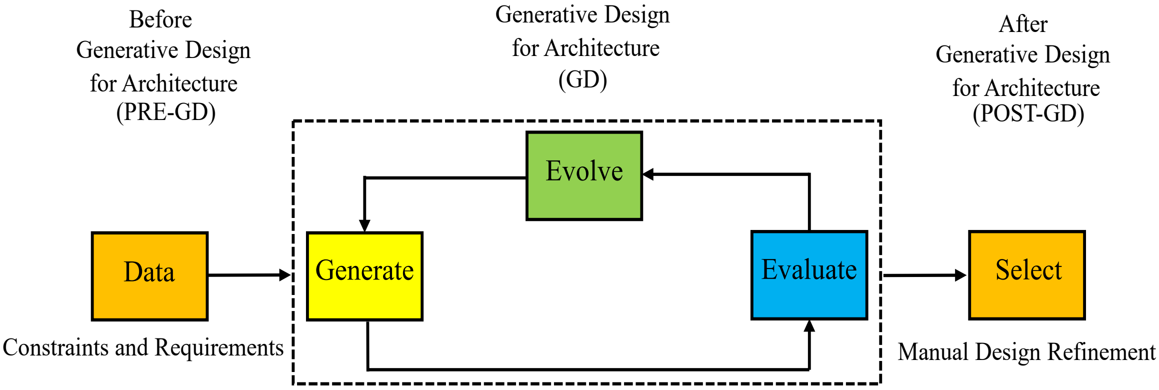

Fig. 3. Generative Design for Architecture Based on Autodesk University Report (Nagy et al. 2018)

As can be seen, in all three definitions provided, the three main components of Performative Computational Architecture are evident: Form Generation, Performance Evaluation, and Optimization. Therefore, the main issue of this research should be introduced in these three sections, which will be addressed below.

2.1. Form Generation

Form generation is a progressive process facilitated by components to discover the optimal geometry of a structure defined in a constant equation (Adriaenssens et al. 2014). The form generation process is one of the most critical stages in conceptual design as it involves decisions regarding determining the value and overall shape of the design. Therefore, the results of form generation provide inputs for all subsequent stages including design, construction, and building lifecycle processes. In the form generation section of the Performative Computational Architecture framework, after data collection, there is a need for a process that can describe a broad design space of possible solutions based on architectural factors and defined criteria (Nagy et al. 2017). This process is introduced in the form of two design structures: parametric design and algorithmic design (Kiss and Szalay, 2020). Moretti (1971) defines parametric architecture as the study of "relationships between dimensions" of a design based on parameters. Kalay (1989) interprets Moretti's (1971) definition of the generative form production process, considering parametric modeling as a computational representation of geometric relationships where, in this process, "the form is automatically updated and visualized on the display by changing the production parameters." Additionally, Terzidis (2006) defines the form generation process in terms of algorithmic design as a method based on describing computer programs that derive from "rule-based logic inherent in architectural programs, typology, building code, and spatial grammar." Therefore, the form generation process in Performative Computational Architecture allows designers to integrate computational complexity and creative computer use (Bakhshi et al. 2022) into the design workflow. Thus, this section of the Performative Computational Architecture process can be defined as a generative algorithm based on a set of parameters and constraints.

2.2. Performance Evaluation

Hubka and Eder (1987) emphasized that traditional design was done using intuition, experience, and judgment. This indicates the need for measuring and quantifying the design capacity to address various needs and enhance the search for design alternatives through multi-dimensional performance values as guiding criteria. With the numerous architectural components, there are many design alternatives in the search space (Gürsel Dino 2012). Hence, finding practical and desirable design solutions during the performance evaluation stage is complex. Therefore, a process of improvement and quality enhancement is necessary to provide designers with continuous feedback on operational performance actions to predict performance accuracy during design (Chegari et al. 2021). With recent advances in digital technology, predictions and numerical assessments of performance aspects can be integrated into the architectural design process to examine how well the design meets requirements (Ekici et al., 2019). Therefore, to strengthen the evaluation process, computational optimization techniques have proven to be effective. Indeed, given the size of the solution space, regular performance evaluation by the designer for each desired design solution is mainly impossible due to time constraints, etc. (Sonta et al. 2021).

Furthermore, a systematic search for solution space based solely on designer experience is challenging (Chegari et al. 2021).

2.3. Optimization

In this section, optimization algorithms are used to optimize the generated designs. The common feature of all these algorithms is drawing inspiration from biological and molecular systems to solve complex optimization problems (Ekici et al. 2019). Among the capabilities of these algorithms are effective exploration of very large spaces, escape from local optima, significant searches in limited time, very low computational costs, and simple mathematics despite problem complexity (Michalewicz and Fogel 2013). In this literature, only specific optimization methods are addressed, focusing on swarm intelligence and evolutionary computations. There are two reasons for this selection. First of all, direct search methods require considerable computational time to deal with various components in an optimization problem (Huang and Niu 2016; Machairas et al. 2014). Secondly, evolutionary methods can provide nearly optimal solutions with multiple design components in an acceptable time (Michalewicz and Fogel 2013). Swarm Intelligence (SI) and Evolutionary Computation (EC) are two powerful optimization methods in evolutionary algorithms. Swarm Intelligence draws from multi-agent intelligent systems inspired by the social behavior of living organisms (Blum and Li 2008) and simulates the behavior accordingly, while Evolutionary Computation uses processes inspired by evolutionary biology and Darwin's theory (Mitchell and Taylor 1999). Therefore, in the research methodology of this study, only studies focusing on swarm intelligence and evolutionary computation approaches have been considered in a comprehensive study.

3. RESEARCH METHODOLOGY

This research adopts a quantitative-qualitative and comprehensive approach based on the subject literature in computational architectural design. Given the research aim, which is a comprehensive analysis based on studies conducted in the field of computational architectural design and the evaluation of components and related objectives. The method of this research involves content analysis of documents with a population of studies conducted in the field of computational architectural design, with an emphasis on evolutionary computations and swarm intelligence in research from around 2002 to 2021 AD. Sampling has been purposeful and structured like a snowball, meaning that with each found article relevant to the topic, other articles were searched based on their references, and the sample size was based on theoretical saturation in each domain. In other words, sampling continued until adding new samples did not contribute new data to the research.

In general, architectural design optimization is only possible through geometric changes in the early stages of design. This clearly distinguishes architectural design optimization from engineering optimization. Therefore, architectural design is mostly referred to as a set of specific boundaries where the search for good engineering solutions takes place. Thus, in the review of the subject literature, only studies that involve geometric changes in architecture have been considered and have not been limited to absolute engineering optimization.

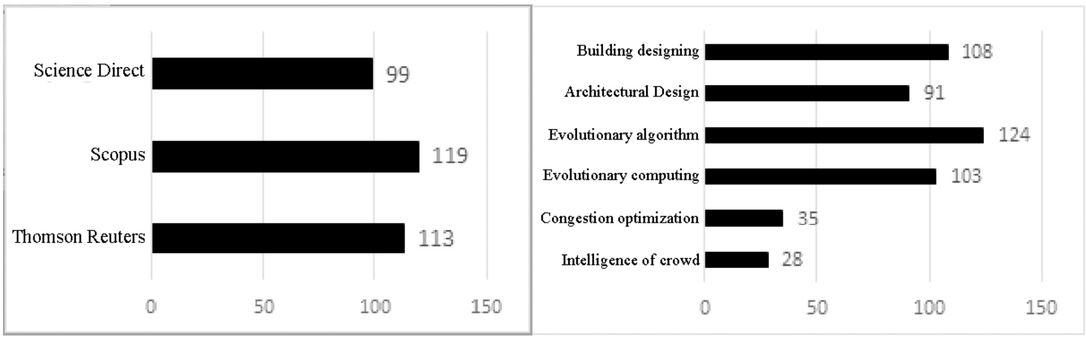

Fig. 4. Keyword Frequency (Right) and Database Frequency (Left) in Reviewed Studies

Multiple articles across a wide spectrum of topics were examined by considering the framework of computational architectural design and evolutionary computation, as well as swarm intelligence. To identify relevant research, keywords such as "building design," "architectural design," "evolutionary algorithm," "evolutionary computation," "swarm intelligence," and "swarm optimization" were utilized (see Fig.s 4 and 6). The search was conducted using databases such as ScienceDirect, Scopus, and Thomson Reuters (see Fig. 4). In total, 119 studies were reviewed, and as depicted in the figure, all reviewed studies are indexed in Scopus journals. Furthermore, 99 out of 119 studies are published in journals indexed in Thomson Reuters. Additionally, the studies were categorized based on the search keywords, as shown in the figure (see Fig. 4).

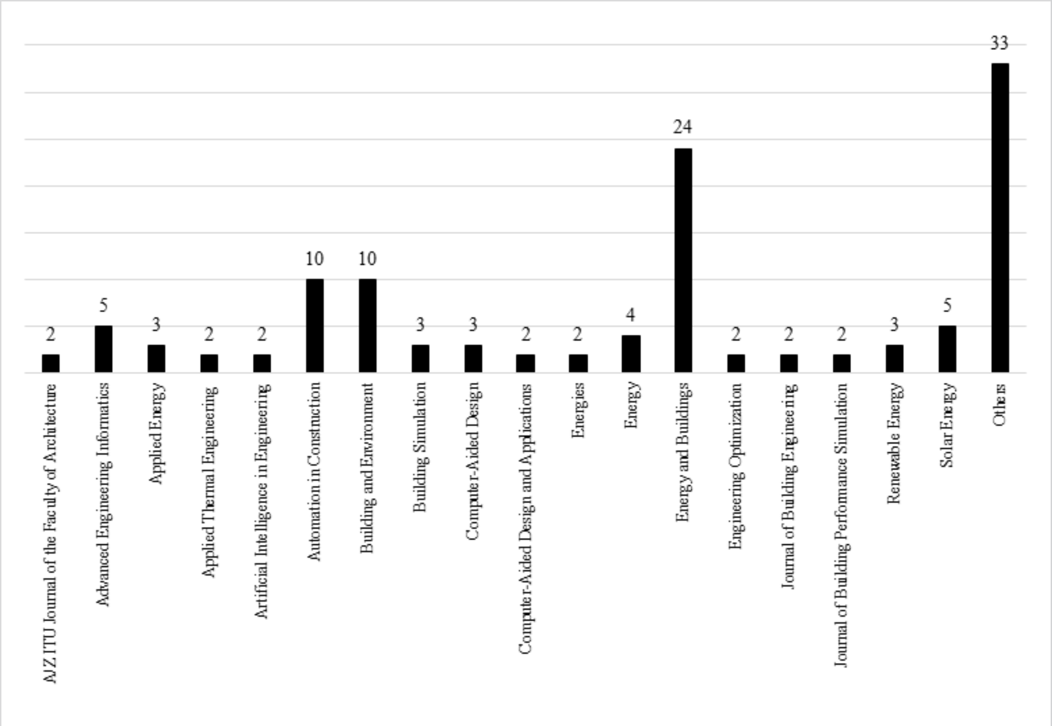

Fig. 5. Frequency of Journals Reviewed in Research Background

For an in-depth examination of this field, there was no time constraint. The completion date for published research was the beginning of January 2021 CE. This extensive search concluded with a collection of relevant articles that include the following criteria:

- Encompassing all three stages of Performative Computational Architecture.
- Clearly addressing the topic of architectural form-finding in both executive and research architectural designs.
- Including optimization processes based on evolutionary and swarm computations (Fig. 6).
- Being published as journal articles, as most conference papers lack essential information.
- Potentially considering any performance metric; there was no specific selection based on particular performance criteria.

The initial investigation of the selected subset ended with identifying another criterion considered for the study of selected articles. Based on this criterion, research papers were selected, and classified under architectural topics including configuration, skin, and building form. This classification, derived from content analysis, was validated by ten energy and architecture experts. Ultimately, the final results were obtained from 39 reputable international journals (Fig. 5). The majority of articles are found in three journals: Energy and Building, Building and Environment, and Automation in Construction, constituting approximately 40% of the articles. This indicates the credibility of the literature review results of this research. Finally, the results underwent correlation analysis tests. In some cases, the significance coefficient exceeded 0.05, which according to statistical experts until 2019 CE would render the test value not significant. However, according to Amrhein et al. (2019), the significance coefficient does not necessarily indicate the significance or insignificance of the data; it is merely a report aiding in this determination.

Based on this, only the reporting of this coefficient has been addressed and it is considered as a variable under investigation. To conduct the correlation test, all data has been encoded and organized in the form of a matrix. To ensure the accuracy of the research process and the validity of the results, the data and findings were provided to ten statistical experts and were confirmed.

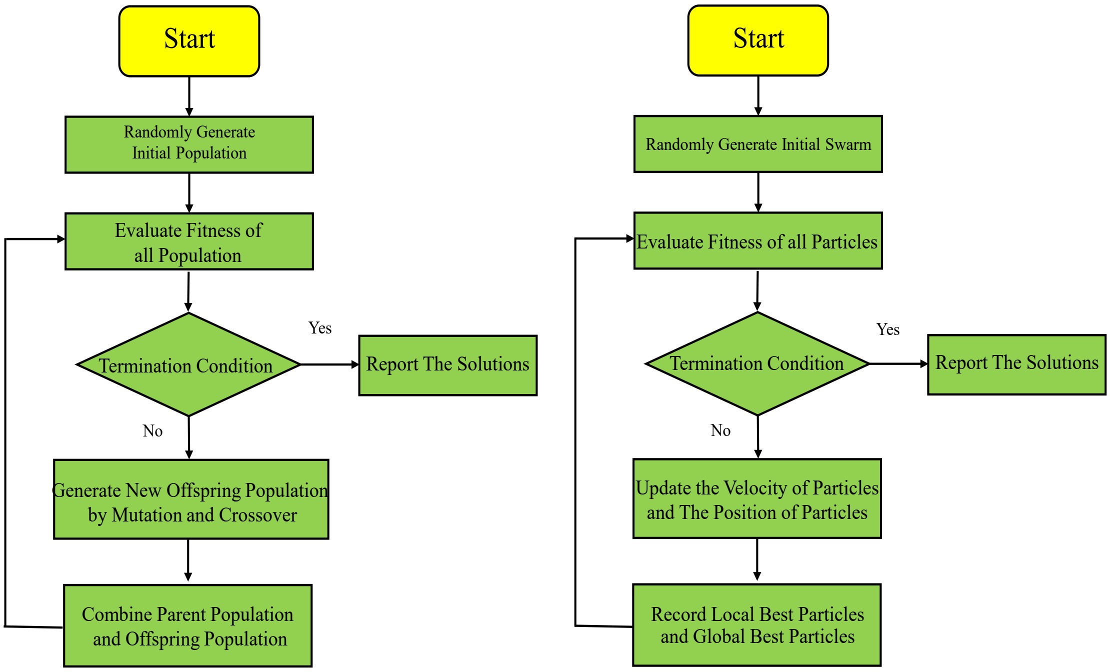

Fig. 6. Swarm Intelligence (SI) and Evolutionary Computation (ES) Processes
(Ekici et al. 2019)

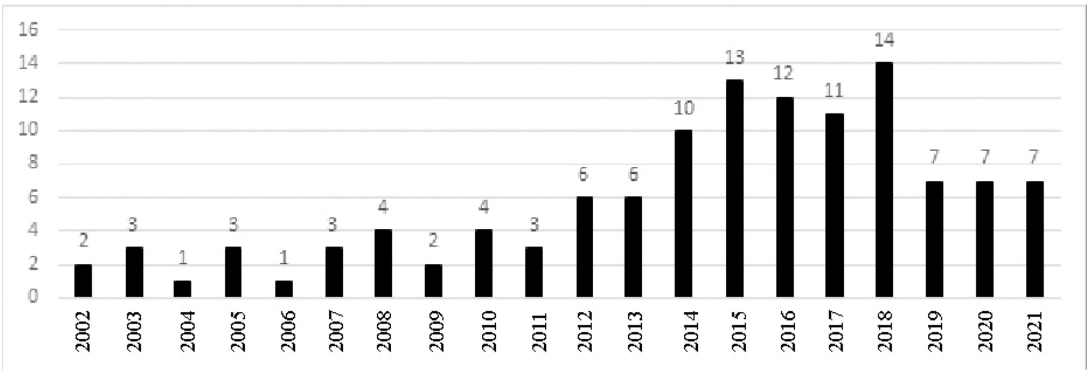

Fig. 7. Timeline of Reviewed Research Studies in Research Background

In this research, architectural and form-finding variables are analyzed concerning the research topics. Optimization is categorized into three topics: building layout, building form, and building skin. The reason for this investigation is their use in drafting generative design algorithms. The variables and parameters of 119 studies in the optimization domain have been obtained. The analysis is presented based on two descriptive and analytical statistics. Descriptive statistics are provided based on all 119 studies under review. In this clustering, form-finding factors consist of 17 variables including window-to-wall ratio, window location, window dimensions, grid matrix, space location, space dimensions, shading, roof structures, roof shapes, orientation, daylighting, floor height, facade design, ceiling design, building shape, number of buildings, and adjacency matrix. The topics include three main subjects: form, skin, building layout, and the publication year of the research from 2002 to 2021 AD (Fig. 7).

4. RESEARCH FINDINGS

Based on the findings, 119 studies have been subjected to content analysis and categorized qualitatively. To ensure validity, the findings have been reviewed and confirmed by ten experts in energy and architecture. Accordingly, the studies are divided into three main topics: form, skin, and layout. Among these, 31 studies focused on building layout, 38 studies on building shape and form, and 70 studies on building skin. It should be noted that some studies target two topics simultaneously. According to the findings, a significant portion of the research has targeted building skin, while spatial layout seems to have received less attention. This could be attributed to the complexity of algorithmic composition in the layout domain compared to the ease of drafting generative design algorithms for building skin.

Furthermore, an examination has been conducted on scales and target uses in various studies. In the investigation of target scales, the majority are related to mid-rise buildings. Among the studies, 66 have examined mid-rise buildings. Additionally, 24 studies have focused on individual spaces (e.g., a room), and 10 studies have addressed high-rise buildings. Moreover, 11 studies have been conducted at the urban scale. A review of the target uses in the studies has also been carried out. In examining the frequency of different uses in the studies under review, administrative and residential sectors have accounted for the most studies, with 31 and 34 cases respectively, reflecting their natural prevalence in construction activities (Fig. 8).

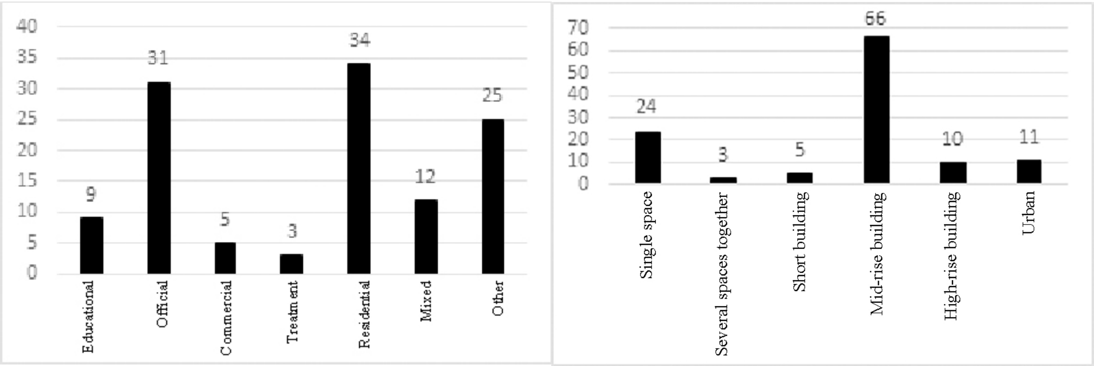

Fig. 8. Frequency of Different Scales Reviewed (Right) and Different Land Uses Reviewed (Left) in Reviewed Studies

However, after examining the general optimization topics, selected studies have been scrutinized based on form-finding factors through content analysis. As observed, among the 119 studies under review, 17 form-finding factors have been extracted, and descriptive and analytical statistics are presented (Fig. 9). The extraction process has been qualitative, and the findings have been validated by ten experts in energy and architecture. According to the figure, the highest frequency is related to the window-to-wall ratio and shading. This is because these two factors have been selected as variables in various studies across all three topics of form, skin, and layout (Fig. 9). The lowest frequency is associated with daylighting and the number of buildings, repeated only once and three times respectively. However, for a more detailed examination, the data of the reviewed studies have been coded in Excel files and then subjected to correlation analysis and Shannon entropy tests. The coding has been binary, with values of zero and one.

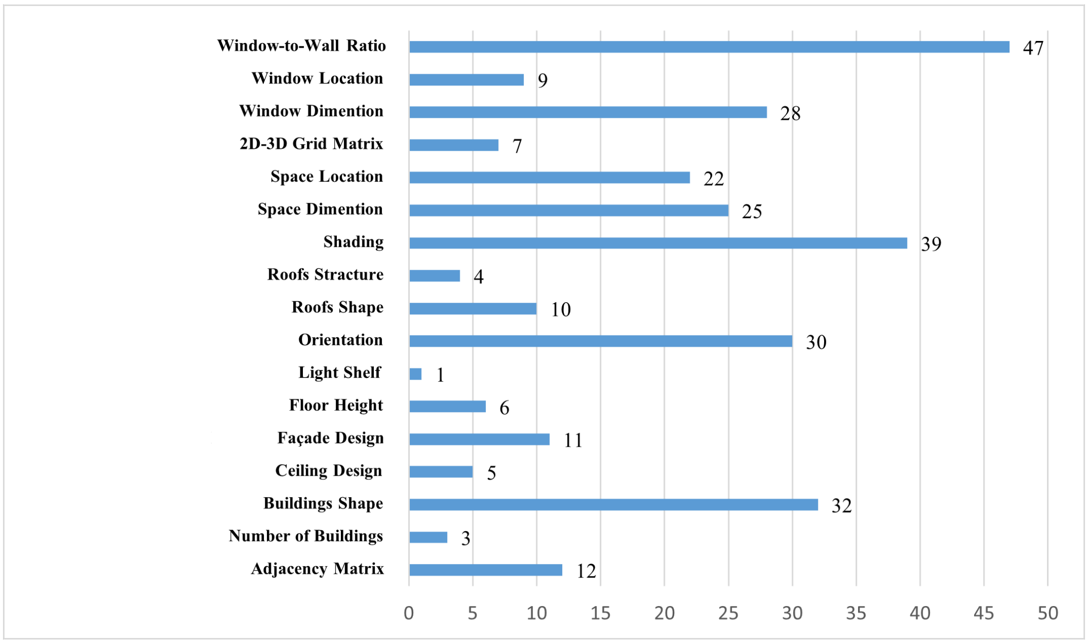

Fig. 9. Frequency of Utilization of Each Form Finding Factor in Conducted Research

Initially, a correlation analysis between form-finding factors and the three main topics was conducted. This analysis aimed to reveal the relationship between each factor and each topic. Pearson and Spearman correlation tests were performed for the form-finding factors with the topic of building form (Fig. 10). The high correlations are associated with floor height, facade design, and building shape. The highest correlation is related to building shape, which seems natural.

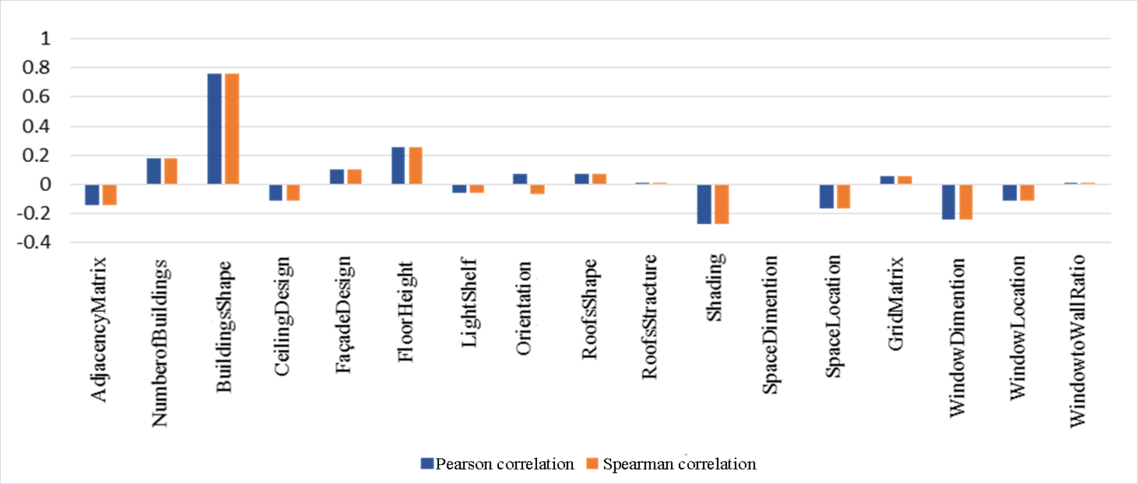

Fig. 10. Pearson and Spearman Correlation of Form Finding Factors with Building Form Topic

Continuing the analysis, Pearson and Spearman correlation tests between form-finding factors and the topic of building skin were evaluated (Fig. 11). In this section, the high correlations are associated with shading, window dimensions, window overhang, and window-to-wall ratio. The highest negative correlation is related to building shape. This indicates that in studies focusing on building skin, the evaluation of building shape has not been considered. Additionally, negative correlations with the adjacency matrix, grid matrix, and space location are observed. Variables such as floor height, facade design, and number of buildings can also be considered as factors in the development of generative design algorithms for building form.

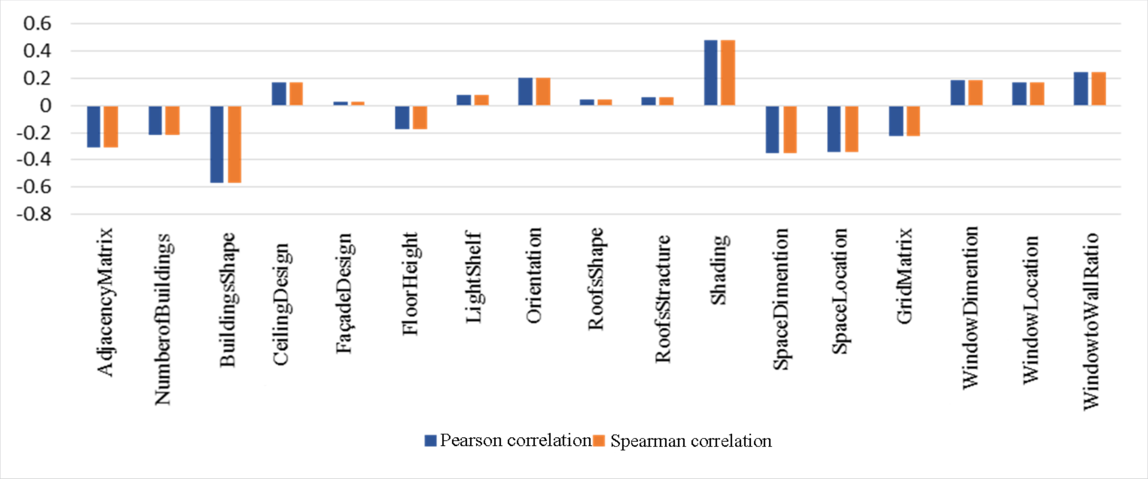

Fig. 11. Pearson and Spearman Correlation of Form Finding Factors with Building Skin Topic

Furthermore, Pearson and Spearman correlation tests between form-finding factors and the topic of building layout, as the focus of this research, were examined (Fig. 12). In this section, the high correlations are associated with the adjacency matrix, space location, space dimensions, and grid matrix. Accordingly, these four variables can be considered as the most significant factors in shaping the algorithm for generating building layouts. The highest negative correlations are related to shading, orientation, and roof shape and structure. This indicates that in studies focusing on building layout, these variables have not been utilized.

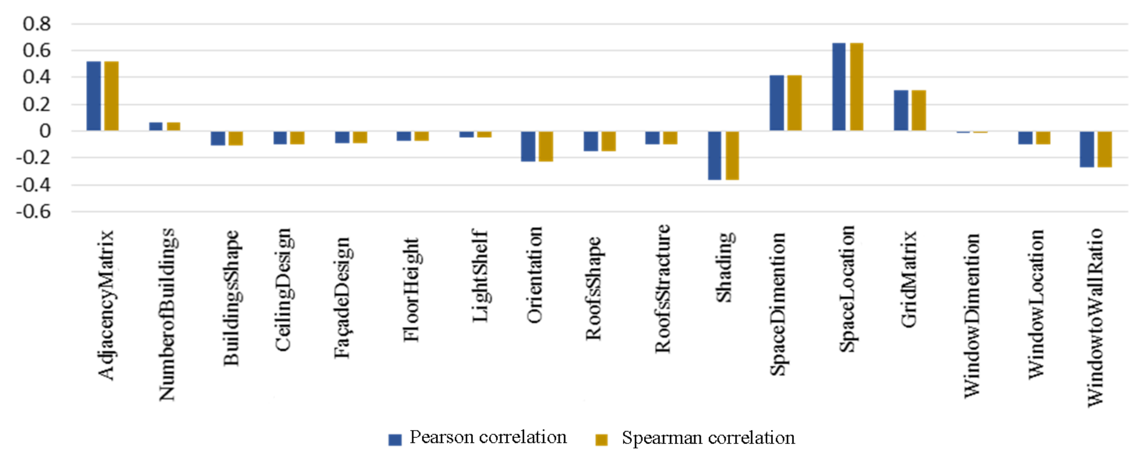

Fig. 12. Pearson and Spearman Correlation of Form Finding Factors with Building Layout Topic

Continuing with prioritizing between form-finding factors and determining the degree of importance for each, the Shannon Entropy method was employed on the selected research data from among the 119 studies (Table 1). This test elucidates the weight of each form-finding factor. As observed in the table, among the 17 mentioned factors, daylighting and roof structure have the highest normalized weights of 0.095 and 0.092, respectively, while shading and window-to-wall ratio have the lowest normalized weights of 0.024 and 0.026, respectively.

Table 1. Frequency Values and Weight of Factors in Shannon Entropy Test

	Window-to-Wall Ratio	Window Location	Window Dimention	Grid Matrix	Space Location	Space Dimention	Shading	Roofs Stracture	Roofs Shape	Orientation	Light Shelf	Floor Height	Façade Design	Ceiling Design	Buildings Shape	Number of Buildings	Adjacency Matrix
Figure code	17	16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1
Weight Factors	0.026	0.065	0.036	0.068	0.040	0.045	0.024	0.092	0.051	0.029	0.095	0.080	0.049	0.068	0.033	0.071	0.059
Factors Frequency	0.165	0.017	0.098	0.026	0.066	0.058	0.160	0.017	0.040	0.116	0.004	0.008	0.049	0.017	0.111	0.013	0.026

For a more detailed examination of the results of the Shannon Entropy test, a weight-frequency coordinate diagram has been plotted. Based on the results, the Shannon Entropy shape has been drawn based on two axes: weight and normalized frequency (Fig. 13). According to the figure, it can be observed that roof structure, daylighting, and floor height have been less examined and are of greater importance for investigation. Additionally, it appears that the window-to-wall ratio, shading, and orientation are of lesser importance and have received less attention.

1	Adjacency matrix
2	Number of buildings
3	building form
4	ceiling design
5	Facade design
6	floor height
7	lighting
8	orientation
9	form of roofs
10	Roof structure
11	shading
12	Space dimensions
13	space location
14	Grid matrix
15	Window dimensions
16	Window position
17	Window to wall ratio

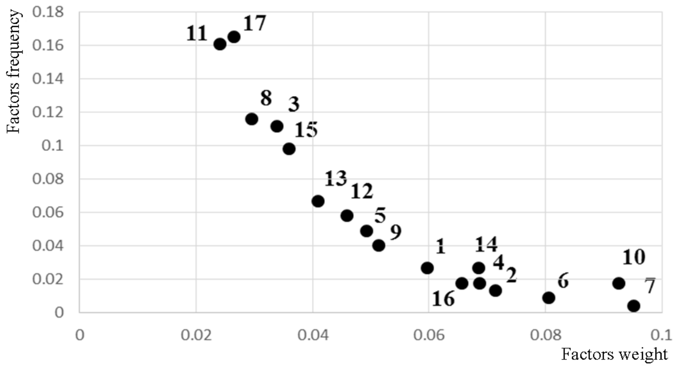

Fig. 13. Shannon Entropy Coordinates Based on Weight and Normalized Frequency Axis

Additionally, the optimization algorithms used in the studies have been examined (Fig. 14). Among the 119 studies, 51 cases utilized genetic algorithms, followed by non-dominant sorting genetic algorithm-II with 31 cases. It is worth mentioning that in 33 studies, two optimization algorithms were used simultaneously. In the diagram, blue represents evolutionary computations, while red represents swarm computations.

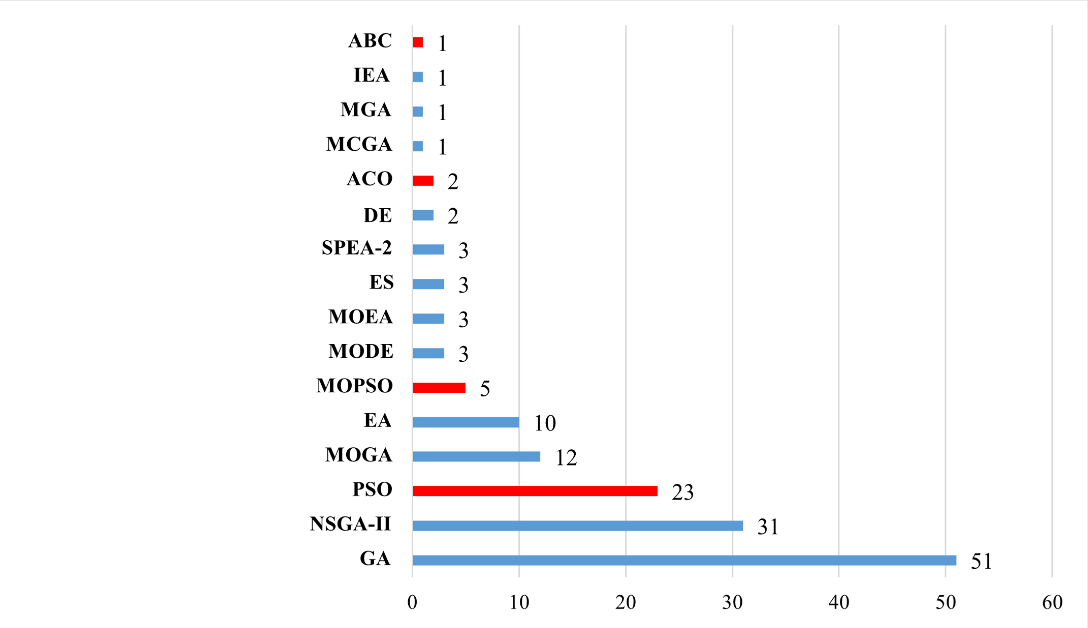

Fig. 14. Frequency of Optimization Algorithms in Reviewed Studies

Furthermore, the functional objectives in computational architectural research have been analyzed. The findings indicate that sustainability has received more attention compared to other objectives, and structures have been optimized less frequently than other topics. About 73% of the topics relate to sustainability, reflecting the contemporary researchers' focus on this area. Structural topics, with only 5 cases and approximately 3%, have been the least optimized functional objective (Fig. 15).

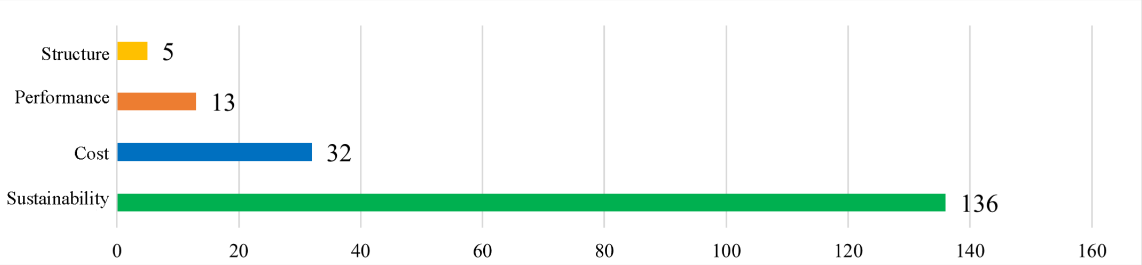

Fig. 15. Performance-based Computational Architecture (PCA) Objectives in Reviewed Studies

Furthermore, subsets of each topic are examined descriptively and analytically (Fig. 16). As observed, energy consumption has received the most attention with 65 research cases, accounting for about 50% of the sustainability-related topics. This highlights the significance of energy-related issues in recent years. The least attention is given to comprehensive costs and energy consumption costs, with only two cases each. The frequency distribution of each functional objective is presented below.

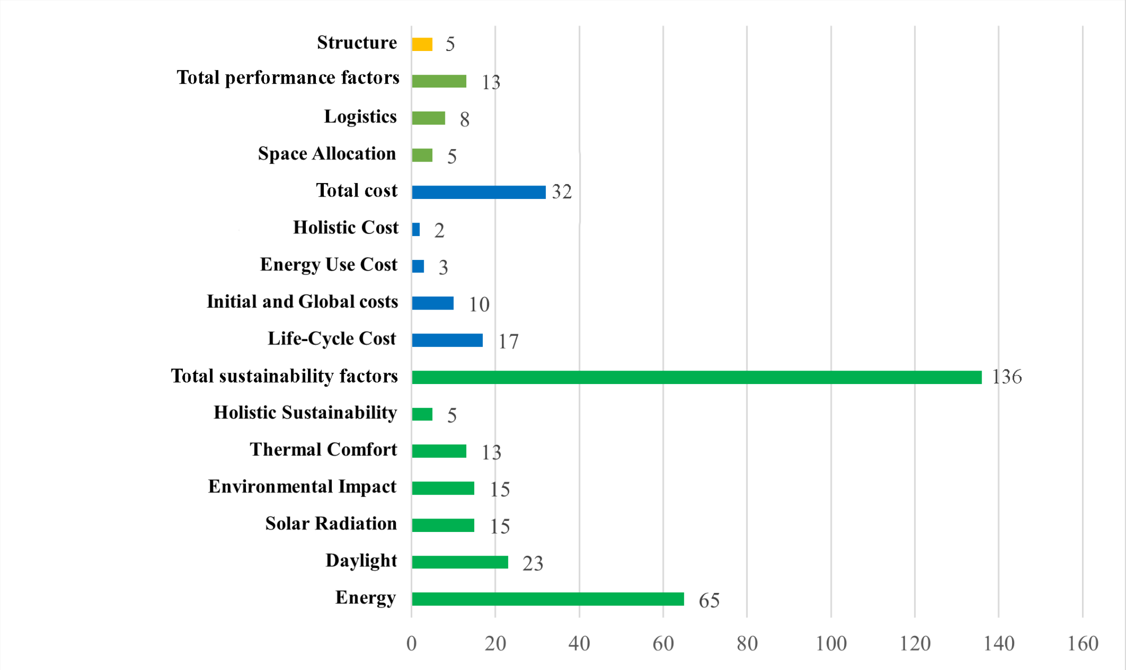

Fig. 16. Frequency of Performance Objectives and their Factors Briefly in Reviewed Studies

After energy consumption, daylighting, life cycle costs, solar radiation, and environmental impacts receive the highest levels of attention, with 23, 17, 15, and 15 cases, respectively. This significant difference in attention underscores the importance of energy consumption among researchers. Furthermore, the least frequent functional objectives are related to comprehensive costs, with only two cases, and energy consumption costs, with three cases. The disproportionate attention highlights a contradiction between the frequency of energy consumption-related topics and energy consumption cost-related topics. As mentioned, life cycle costs are the most attended to in the cost category, with 17 cases, followed by global and initial costs, with 10 cases, having the highest frequency.

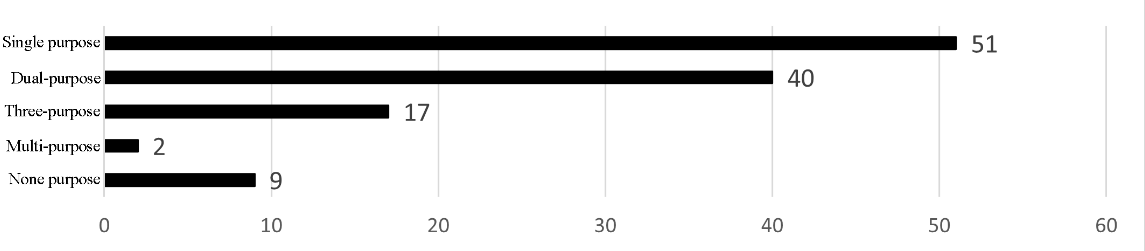

Fig. 17. Frequency of Performance Objectives States in Research Studies

Some of these objectives are jointly optimized in research studies. For example, energy consumption and daylighting have been considered together as performance objectives in many studies. Therefore, research studies are categorized based on the number of performance objectives optimized (Fig. 17). 51 studies have investigated only one objective, while 40 studies have jointly optimized two objectives.

Table 2. Two-dimensional Matrix of Frequency of Common Performance Objectives in Reviewed Studies

	Structure	Logistics	Space Allocation	Holistic Cost	Energy Use Cost	Global costs	Life-Cycle Cost	Holistic Sustainability	Thermal Comfort	Environmental Impact	Solar Radiation	Daylight	Energy
Energy	1				1	8	6		7	2	2	15	21
Daylight	2					1			3			4	15
Solar Radiation													2
Environmental Impact						2	7		1	3			2
Thermal Comfort							1			1		3	7
Holistic Sustainability													
Life-Cycle Cost									1	7			6
Initial and Global costs						3				2		1	8
Energy Use Cost													1
Holistic Cost													
Holistic Cost													
Logistics		1											
Structure												2	1

Based on this and to recognize common objectives in the researches, a two-dimensional matrix has been presented, which can be observed in Table 2. As seen in the two-dimensional matrix, the majority of shared objectives relate to energy consumption and daylighting, with 15 research studies. Following that, energy consumption shares eight common objectives with initial and global costs. Additionally, energy consumption has been jointly optimized with life-cycle costs and energy use costs in six research studies.

5. CONCLUSION

This study provides a review analysis of performative computational architecture using evolutionary and swarm computations. This topic has been under discussion among architects and engineers over the past decades. Based on the evidence presented in the findings, it can generally be concluded that attention to performative computational architecture among architectural researchers is increasingly growing. This is particularly noticeable in architectural discussions involving complex computations, such as thermal energy, lighting, and costs.

The findings from document analysis indicate that performative computational architecture, due to the combination of generative architectural design and optimization computations, has significant conceptual ambiguities. These ambiguities are much more prevalent in domestic studies, which are very few. Therefore, in this study, a conceptual framework for algorithmic design, generative design, and parametric design has been proposed (Fig. 18) to alleviate terminological confusion. The proposed conceptual framework suggests that generative design requires explicit use of an algorithm that generates a design. Moreover, if the algorithm meets the traceability criterion, meaning there is an identifiable relationship between the algorithm and the generated design, then algorithmic design is also considered. Finally, if the design depends on a set of parameters, it is a parametric design.

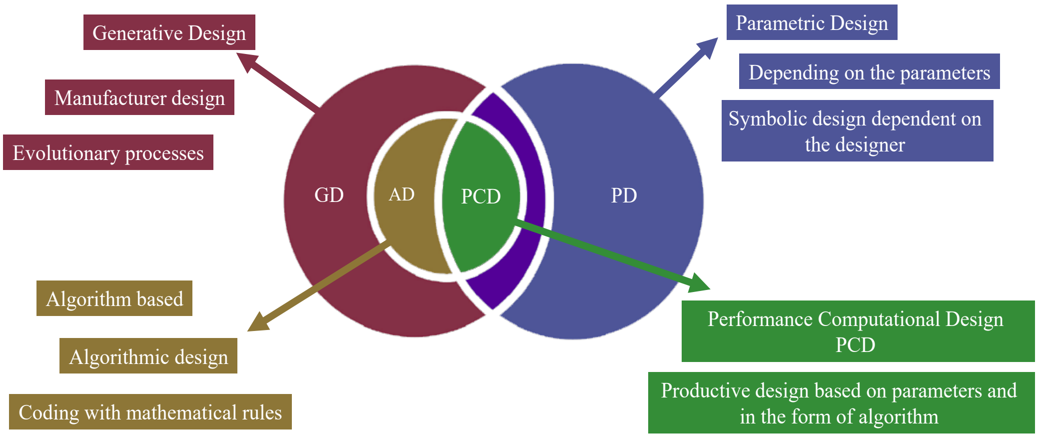

Fig. 18. Comparative Analysis of Four Generative Design (GD), Algorithmic Design (AD), Parametric Design (PD), and Performative Computational Architecture (PCD) Concepts with Considerable Overlaps

Although each term can be defined separately, there is a significant overlap among the concepts, which is the main reason for their incompatible use. The plotted diagram (Fig. 18) effectively demonstrates this overlap. According to the figure, algorithmic design is a subset of generative design and has a non-empty intersection with parametric design. Additionally, parametric design is orthogonal to other terms. For example, an algorithmic design approach that uses algorithms with parameters is also an example of parametric design; for instance, one can refer to an algorithm that creates a facade based on a set of parameters, such as its overall dimensions and the size and distribution of different facade elements. However, performative computational architecture, as an approach, is formed based on performance-based design. The main boundary of this concept with three other concepts is the focus on performance evaluation and optimization.

Moreover, the findings obtained from the two correlation and Shannon tests have been comparatively examined for prioritization (Table 3). Based on the findings, it can be concluded that the topic of building skin has received more attention from researchers in recent years compared to other topics. The reason for this is the significant impact of building skin on sustainability and energy discussions, as well as the simplicity of the generative design algorithms for skins. Factors related to windows, such as dimensions, location, and window-to-wall ratio, are particularly noteworthy in this regard. Two other topics, namely building form and layout, are also among the most common architectural research topics. In the layout topic, factors related to spatial organization have received more attention than other variables, and in the building form topic, aesthetic considerations have been emphasized.

Table 3. Prioritization of Form-finding Factors Relative to Performative Computational Architecture Topic

The Subject of Design	Building Form					Building Shell						Building Configuration			
Physical Factors in order of Priority	Buildings Shape	Floors Height	Number of Buildings	Façade Design	Roof Shape	Shading	Window-to-Wall Ratio	Orientation	Window Dimention	Ceiling Design	Window Location	Space Location	Adjacency Matrix	Space Dimention	Grid Matrix
Correlation	0.75	0.25	0.18	0.10	0.08	0.45	0.25	0.20	0.19	0.18	0.18	0.65	0.50	0.40	0.30
Shannon's Weight	0.033	0.080	0.071	0.049	0.051	0.024	0.026	0.029	0.036	0.068	0.065	0.040	0.059	0.045	0.068

Based on these findings, the main architectural variables for optimization can be elucidated as form, skin, and building layout for the development of a generative algorithm. According to the findings, floor height, facade design, and the number of buildings can be considered as factors for composing the generative algorithm for building form design. In the domain of building skin, shading, window dimensions, window layout, and window-to-wall ratio are the most important architectural variables for generative design. In the context of building layout, high correlations with topics related to adjacency matrix and connectivity, spatial location, space dimensions, and grid matrix are observed. Spatial location, adjacency matrix, and grid matrix are among the most significant factors in shaping the generative algorithm for building layout design.

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CONFLICT OF INTEREST

The authors have no conflicts of interest to declare.

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