博士論文

EMPIRICAL RESEARCH ON HUMAN-AI COLLABORATIVE ARCHITECTURAL DESIGN PROCESS THROUGH A DEEP LEARNING APPROACH

AI

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Content

Preface

As the amount and scale of buildings continues to expand globally, the energy crisis is becoming increasingly severe. According to the International Energy Agency (IEA), the building and construction (B&C) sector accounts for 36% of total global carbon emissions. In response to this issue, the architectural community has begun to advocate sustainable building design to reduce carbon emissions by optimizing the energy efficiency and environmental impact of buildings. Although building performance design has become a mainstream design philosophy, there are still many challenges, the most prominent of which are the arithmetic limitations and the lack of digitization.

The contemporary architectural design paradigm of performance design still requires extensive data analysis, simulation and optimization operations, which are demanding in terms of computer performance and algorithms. However, the simulation arithmetic power of a single silicon-based computer has almost reached its limit and is increasingly unable to meet the demands of increasingly complex architectural designs. At the same time, the global B&C industry has a relatively low level of digitization as well as a lack of efficient data management and processing systems. These issues have constrained the development of performance-based building design and seriously affected the sustainable development of the industry.

In this context, the rapid development of artificial intelligence (AI) technology has provided new ideas and methods to solve these problems. AI technologies have been widely used in other industries, such as healthcare, finance and manufacturing. In recent months in particular, AI-generated content (AIGC) technology is experiencing a Cambrian explosion, rapidly sweeping every area of social life. Countless people with doubts in mind can't help but secretly lined after really experiencing ChatGPT, MidJourney: " It might really be coming this time."

In the blossoming AIGC ecology, the progress of architectural design AIGC is relatively backward. The essential reason is that the data structure of architectural models is more complex, and the method of encoding structured information of buildings still has great potential for development. However, it cannot be ignored that AI is gradually and profoundly affecting the workflow of architectural design, making the architectural design process shift to the Human-AI collaborative design paradigm. On the one hand, the rapid development of AI technology provides new opportunities for rapid solutions to building energy consumption problems. On the other hand, how to adapt and collaborate with AI technologies in design practice requires continuous thinking and practice by architects and technicians. It is hoped that the findings of this thesis will provide new ideas and methods for the fields of architecture, computer science and AI, and promote the development of interdisciplinary research.

Abstract

In the current era of digitalization and information technology, the rapid development of technology has a profound impact on architectural design. Traditional architectural design paradigms are often limited to personal experience and subjective consciousness, making it difficult to comprehensively analyze and synthesize various factors and needs. the emergence of AI technology provides a new approach and method for architectural design, injecting more creative and sustainable potential into the design process.

The purpose of this thesis is to explore how AI technologies intervene in the architectural design process and to discuss the importance and approaches that drive the paradigm shift towards human-AI collaboration in architectural design. The research will be conducted from two perspectives: theoretical and practical. At the theoretical level, how AI technologies affect architectural design through technological evolution will be analyzed, as well as the advantages, disadvantages and trends of different AI networks in sustainably analyzing and optimizing different kinds of architectural designs. Further, based on this, the methodology of how to develop a reflection on the nature of technology and data will be discussed. At the practical level, AI methods that are inventive and capable of performance-based design will be constructed and trained. And the basic process of human-AI collaborative architectural design will be presented with an empirical study.

The results of this thesis will not only provide a theoretical reference and methodological basis for future research on human-AI collaborative architectural design at a broader and higher level, but will also attempt to explore new ideas and methods for the field of architectural design during the evolution of the old and new paradigms, ultimately realizing the purpose of sustainable development of the B&C industry.

Keywords: deep learning; artificial intelligence; architectural design paradigm; building design solution grneration; collaborative design

Chapter 1. Research Background and Purpose

1.1. Introduction

This chapter aims to build the context of this research and to develop an initial perception of the subject matter and instrumental approach.

The current state of the energy crisis in the B&C industry will be revealed first. After that, the limitations of the current performance-based architectural design paradigm and the potential development of the human-machine collaborative architectural design paradigm will be analyzed from the literature and historical perspectives, respectively.

Subsequently, the motivation of this research is presented: to study a deep learning-based approach to adapt the human-ai collaborative design paradigm. The ultimate goal is to leave the "strong logic" and "strong computation" parts to AI, unleashing the creativity of architects and improving the efficiency and performance of architectural design.

Finally, a specific operational framework for the research stages is formulated to address the three issues of " Approach Toolbox", "Approach Construction", and "Approach Validation".

1.2. Research Background

1.2.1. A New Record of Energy Crisis

Energy is a fundamental guarantee for human survival and development and serves as the foundation for socio-economic progress. As society rapidly advances, the total energy consumption continues to rise. In recent years, energy consumption in the construction industry has consistently accounted for nearly 40% of global energy consumption.

The latest assessment report released by the Intergovernmental Panel on Climate Change (IPCC) for the Working Group on Climate Change Mitigation, AR6 WGIII, gives a clear message that the B&C (B&C) industry has significant potential to meet the global mitigation targets of the Paris Agreement. Potential opportunities include improving the efficiency and use of existing buildings, improving the energy efficiency of new buildings, the adoption of efficient lighting appliances and equipment in buildings, renewable energy integration in buildings, and decarbonizing the production of building materials. The consensus from the IPCC report is that operational emissions from buildings need to be reduced by more than 95% compared to current levelness decline(1). And these declines are cost-effective and beneficial to building occupants and energy security.

In 2020, the global spread of the COVID-19 pandemic led to unprecedented changes in the B&C industry worldwide. These changes include a significant decrease in construction demand in major economies, work stoppages due to pandemic-related lockdowns, labor and material shortages, changes in work patterns, and the challenges in managing increased energy burdens. All these situations persist today, resulting the largest decrease in carbon dioxide emissions over the past decade(2).

In 2021, the construction activities of most major economies have rebounded to pre-COVID-19 levels. Workplaces have reopened. But the hybrid work model still exists. The energy-intensive use of buildings has increased, and more emerging economies have increased their use of fossil fuel gases in buildings. The Buildings Climate Tracker (BCT), a global tracking system for the B&C sector, shows that decarbonization activities for buildings have recovered to their previous rate since the pandemic. In 2021, the demand for building energy increased by approximately 4% compared to 2020, reaching 135 EJ, the largest growth in the past decade(3). This observation indicates that since 2020, decarbonization in the B&C industry has experienced a negative rebound, with energy intensity and emissions increasing. This has resulted in an increasing gap between the observed energy efficiency and the required path.

The decarbonization level decreased from its 2020 peak of 11.3 to 8.1. The gap has widened from 6.6 points in 2019 to 9.0 points in 2021 (Figure 1).

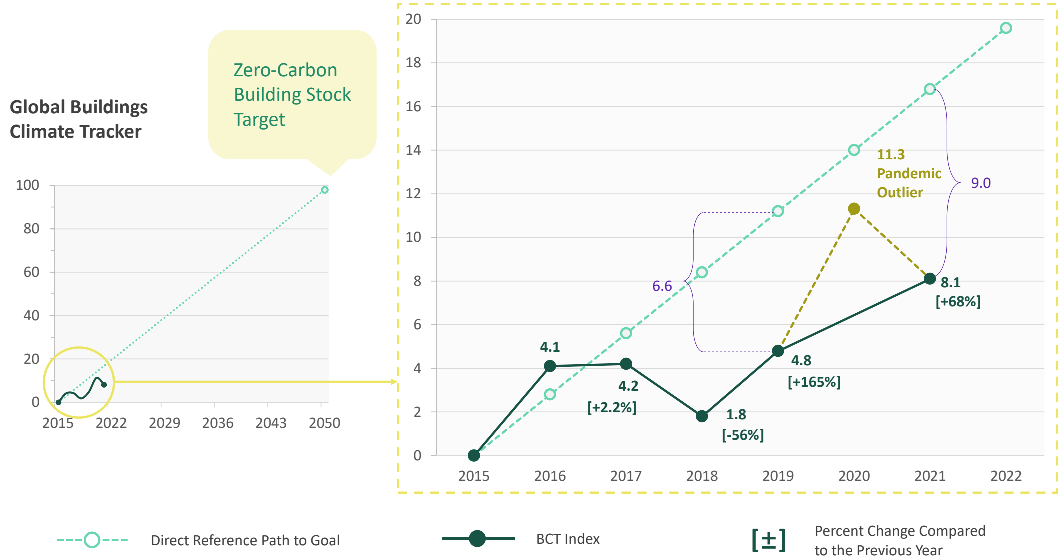


Figure 1. Direct reference path to a zero-carbon building stock target in 2050 (left); zoom into the period between 2015 and 2021, comparing the observed Global Buildings Climate Tracker to the reference path (right). Data Source: Adapted by the Buildings Performance Institute Europe (3).

The result of this trend is that the carbon dioxide emissions generated by building operations have reached their highest historical levels, approximately 10 billion tons of carbon dioxide, an increase of around 5% from 2020 and 2% higher than the previous peak observed in 2019. If the estimated emissions of about 3.6 billion tons of carbon dioxide from the production of building materials (e.g., concrete, steel, aluminum, glass, and bricks) are included, the B&C industry account for about 37% of global emissions in 2021(3).

In the year 2022, due to the Russia-Ukrainian War and the consequent European energy crisis, the path towards decarbonization and carbon reduction is inevitably arduous. Further risks are posed by the fluctuating global energy prices, the cost-of-living crisis faced by various economies, and the impact of rising interest rates on decarbonization investments in buildings by governments, households and businesses. BCT has monitored the progress of the construction industry in achieving the goals set by the Paris Agreement. The updated data from the system in 2022 confirms this observation and indicates that the actual climate performance of the industry is increasingly diverging from the necessary decarbonization pathway. The B&C industry is still unable to achieve decarbonization by the year 2050(4).

Currently, China remains the world's largest B&C market. China's B&C industry consumed 2.147 billion tce for the whole life cycle in 2018, accounting for 46.5% of the national energy consumption. Notably, in 2019, energy consumption in residential buildings accounted for approximately 62% of the total energy consumption. According to the "2022 China Urban and Rural(5), the total energy consumption of the national construction process in 2020 was 2.27 billion tce, accounting for 45.5% of the total national energy consumption (Figure 2).

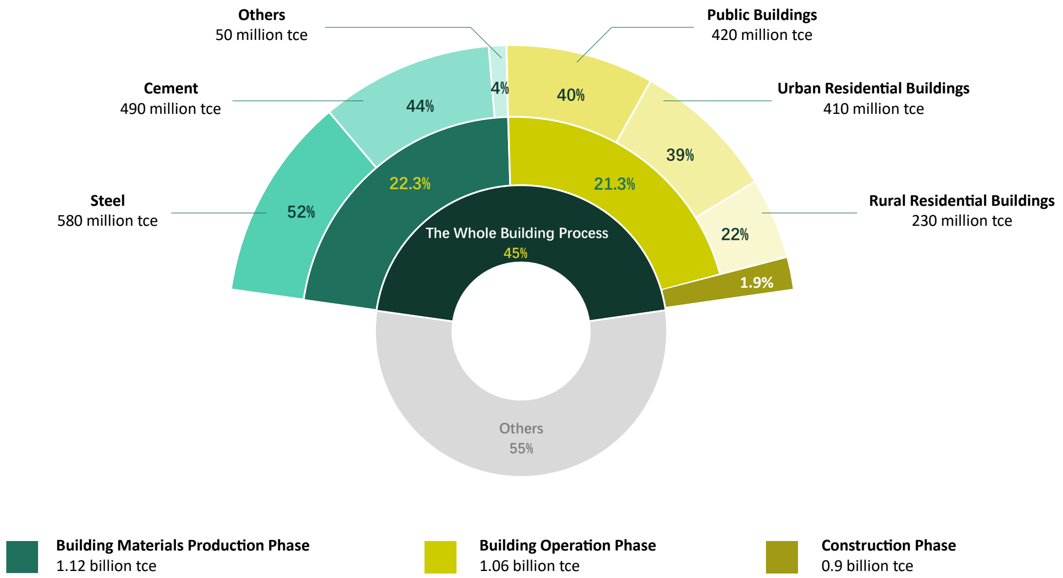


Figure 2. Energy Consumption and Proportion of The Whole Building Process in China in 2020.

According to the report's calculations, from 2005 to 2020, the total energy consumption in the entire process of construction in China has increased from 930 million tce to 2.233 billion tce, a 2.4-fold increase with an average annual growth rate of 6.0%. The average annual growth rates during the "11th Five-Year Plan", "12th Five-Year Plan", and "13th Five-Year Plan" periods were 5.9%, 8.3%, and 3.7%, respectively (Figure 3).

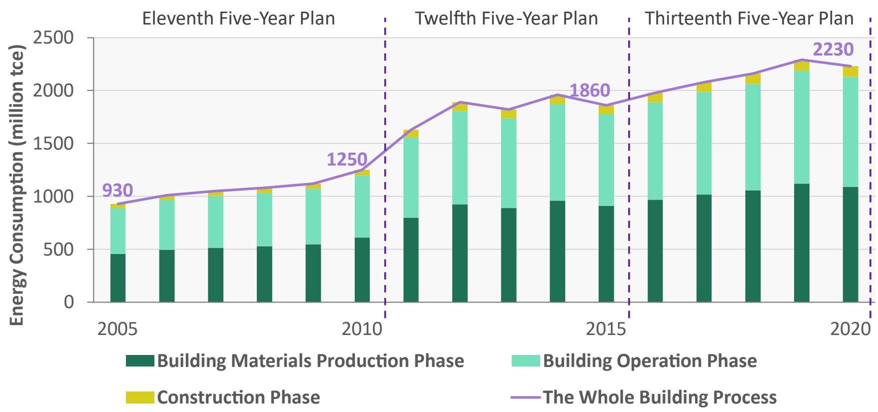


Figure 3. Energy Consumption of the Whole Building Process in China (2005-2020).

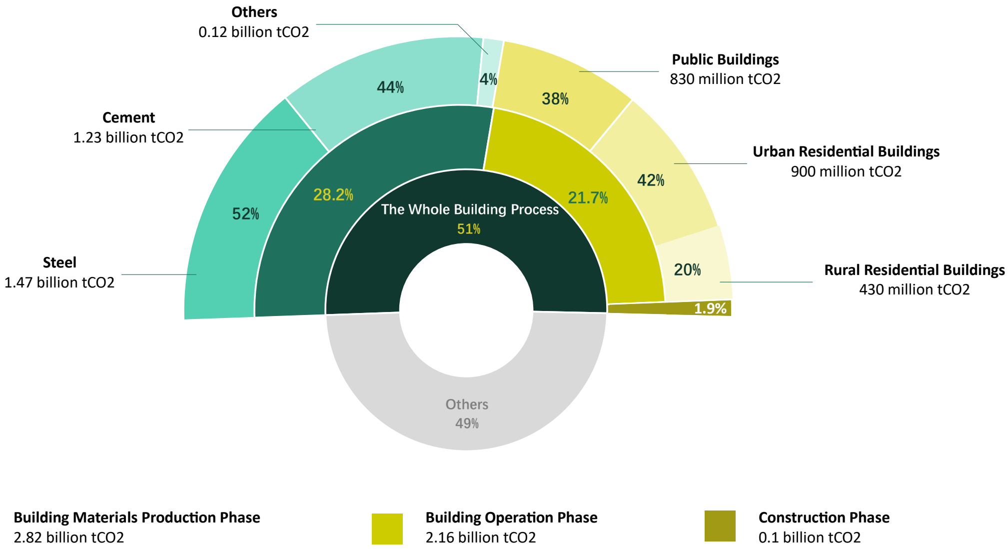


Figure 4. The Total Carbon Emissions and Proportions of China's B&C Process in 2020.

In 2020, carbon emissions from public buildings, urban residential buildings, and rural residential buildings were 834 million t CO_2, 901 million t CO_2, and 427 million t CO_2, respectively. They accounted for 38.6%, 41.7%, and 19.8% of the total carbon emissions from buildings (Figure 4). Due to the impact of the COVID-19 pandemic, carbon emissions from public buildings decreased compared to 2019, while the opposite was observed for residential buildings, where the increasing trend was more apparent. This is consistent with the reality that under the pandemic, the energy consumption of public places such as shopping malls and office buildings decreased due to lockdowns, while people worked more from home, leading to an increase in energy consumption in residential buildings (Figure 5).

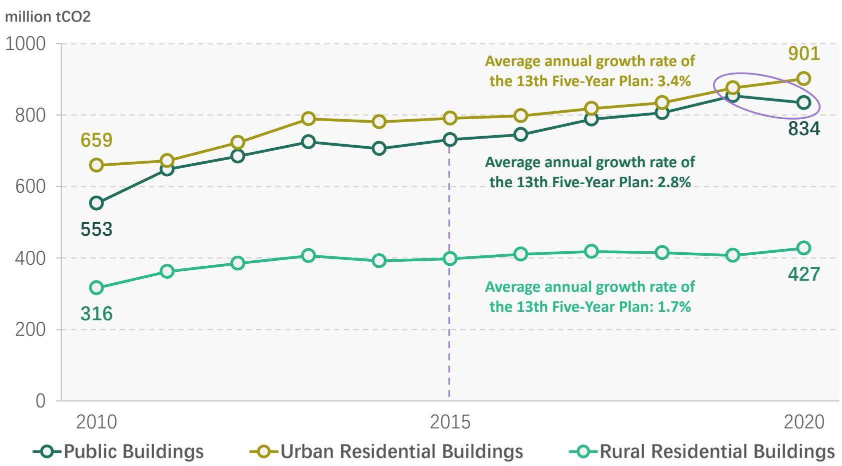


Figure 5. Emission Trends by Building Type.

In conclusion, it is evident that energy-effect buildings play a crucial role in reducing global energy consumption. The construction of low-energy and high-comfort healthy living environments is a necessary choice for energy conservation, emission reduction, and green development. This has become an important goal in contemporary residential building design and construction, especially for low-rise, small-scale, and decentralized housing, as well as in underdeveloped areas with limited energy infrastructure, such as nature reserves, small towns, and new rural construction. Therefore, the construction of "low-energy" or even "ultra-low-energy" residential buildings is imperative.

1.2.2. A Fatigue in the Current Architectural design Paradigm

The emergence of Computer-Aided Design (CAD) in the 1960s marked the beginning of the digital era in architecture. Computer-Aided Architectural Design (CAAD) is an important branch of computer-aided design that applies computer technology to the design processes of urban, landscape, architectural, and interior design. The evolution of CAD and CAAD systems has led to the ongoing optimization and progression of digital technologies in the field of architecture. These advancements have progressed from the initial stage of basic 2D drafting towards the multidimensional support of design ideation and the entire design process. Furthermore, these technologies have shifted from merely improving drafting quality and efficiency towards fostering innovative design and enhancing overall project benefits. As such, the development of digital technologies has brought significant changes to architecture, and its impact will continue to be felt in the future. Over the past few decades, the development of digital technologies has not only impacted the processes of architectural design and construction, but also triggered transformative changes within the discipline of architecture itself.

As the demand for energy conservation and emissions reduction in buildings continues to grow, performance-based design has become an important research method and approach in green building design. In recent years, numerous studies have focused on the application and theoretical research of performance-driven optimization in green building design. The performance-based design approach not only ensures the basic functions and spatial requirements of buildings, but also promotes the reduction of carbon emissions throughout the entire lifecycle of buildings.

The Development of Performance-Based Architectural design

The concept of "performance" in architecture can be traced back to the three principles of "solidity, usefulness, and beauty" described by Vitruvius in his "Ten Books on Architecture".

These principles represent the three performance demands of architecture in terms of structure, function, and form(6). However, in the subsequent history of architecture, these three performance demands were gradually replaced by the formalism of aesthetics, which resulted in the loss of the potential for performance to guide architectural creativity. In the late 18th and early 19th centuries, with the development of cities, the evolution of technology, and cultural changes, modern architecture gradually freed itself from the constraints of classical aesthetics. By utilizing new materials and technologies, the performance of architecture was reintroduced into the field of architecture, leading to a new era of modern architecture. Gaudi's hanging chain model and Frei Otto's tensile structures based on dynamics are both typical examples of designs based on performance.

In 1982, Gibson first explicitly proposed the concept of performance-based design at the W60 conference of the International Association for Bridge and Structural Engineering, stating that "performance-based design is first and foremost a practice of thinking and working, rather than a means to an end. It is concerned with what a building needs to do, rather than dictating how it should be built." Since then, performance-based design has been widely applied in the fields of fire and structural engineering(7). However, this field of research is beyond the scope of this study.

Scholars have different emphases on the definition of performance-based design. Machairas et al. believe that optimization is the process of finding the minimum or maximum value of a function by selecting variables that are subject to certain constraints. The optimization function in building design is referred to as cost, fitness, or objective function, and is typically calculated using simulation tools(8).

In recent years, with the development of computer technology, performance-based design has been further developed in architectural design and its related fields. Many researchers have been developed compared with the general performance-based approach. The main manifestation is that performance-based design has gradually developed into a way of viewing design problems through a holistic approach. Some of the representative ones include Professor Yimin Xie's study of bi-directional progressive structural optimization method "Evolutionary Topology Optimization of Continuum Structures: Methods and Applications"(9), Phillip Yuan's " Environmental performance-based building autogenous form design combined with physical wind tunnel", and the study of "Thermodynamic Architecture" by Kiel Moe, et al., (10,11).

It can be observed that performance-based design has subverted the traditional "empiricism" in architectural form optimization and has deepened the application of quantitative analysis tools in the design process. This has strengthened the generation logic of architectural form and promoted the cross-disciplinary integration between architecture and related fields.

The Introduction of Performance-Based Methods in Green Building

Research related to green buildings has gone through 3 stages over time, from on-site measurements, physical model simulations to current computer numerical simulations(8). Green building performance includes lighting and daylighting, acoustic environment, wind environment, indoor thermal environment, indoor ventilation, and indoor air quality, among others. These performance indicators can all be expressed in specific numerical values and have the conditions for quantitative optimization. Building energy consumption is not only related to the building's own conditions, such as thermal performance and equipment system compatibility, but also closely related to external climatic conditions, indoor set benchmarks and other environmental factors. Therefore, it is essential to design buildings appropriately in conjunction with local climatic conditions to achieve energy savings and emission reductions.

Traditional green building designs employ an "empirical" design approach, which reduces building energy consumption through traditional techniques such as shading the exterior façade, green roofs, and wind-driven atria. However, the actual effectiveness of such designs throughout the building's lifecycle remains to be verified, and they are difficult to adapt to the unique and complex situations of buildings. Performance-based green building design is a scientific and quantitative design approach that requires the entire process to be guided by clear performance goals. The essence of this approach is to use clear logic to construct building performance goals so that the design can be optimized towards these goals in a beneficial manner, ultimately meeting the requirements of green building design goals. Based on different optimization methods and the number of optimization factors used during the simulation process, Zhou Hao and his colleagues have summarized performance-based green building design methods into 3 types: manual iterative optimization mode, single-objective automatic optimization mode, and multi-objective automatic optimization mode. Among them, single-objective and multi-objective automatic optimization are two types of digital performance optimization methods. By delegating the optimization process to computers, optimization efficiency can be greatly improved, and optimization goals that are difficult to achieve manually can be realized.

The current state of research in the field of performance-driven digital green building design can be categorized into 3 levels: building envelope, building spatial forms, and building cluster relationships. An analysis of these levels provides a comprehensive overview of the evolution of research in this field.

Building Envelope

Among the existing studies, the optimization of the performance of building envelope (Table 1) has primarily focused on the application of passive energy-saving technologies in building envelopes. Since the enactment of EU Energy Performance of Buildings Directive 2002//91/EC regarding envelope structures in 2002, the number of studies on improving the performance of building envelope structures in EU member states has sharply increased. Early research primarily combined building envelope structures with building form and used genetic algorithms for related research. In 2003, Caldas et al. focused on multi-objective optimization problems by reviewing the basic principles of genetic algorithms and used performance optimization methods to determine the size and location of windows, generate building walls, generate building forms, and design and operate HVAC systems for several building envelope structures(12). In 2009, Daniel Tuhus-Dubrow et al. combined optimization algorithms with building energy simulation engines to select optimal values for comprehensive parameters related to residential building envelope structures and building forms(13). They also compared the accuracy and efficiency of three optimization methods, including genetic algorithms, sequence search techniques, and particle swarm optimization, under different envelope structure parameters. Additionally, Daniel Tuhus-Dubrow et al. developed a simulation optimization tool that combines genetic algorithms with building energy simulation software to select optimal values for parameters related to the building envelope structure and minimize the energy use of residential buildings(14). Their research primarily focused on building form and concluded that rectangular and trapezoidal buildings always have the lowest life cycle costs.

Table 1. Typical Literature for Building Envelope Performance Optimization.

Category	Year	Authors	Building Types	Algorithms
Morphology	2003	Caldas L G,Norford L K. (12)	-	Genetic Algorithm
	2009	Daniel Tuhus-Dubrow, et al. (13)	Residential Building	Genetic Algorithm, Sequence Search and Particle Swarm Techniques

Category	Year	Authors	Building Types	Algorithms
Sound, Light and Thermal	2010	Daniel Tuhus-Dubrow, et al. (14)	Residential Building	Genetic Algorithm
	2020	Abdel Rahman Wael Salah Mansour(15)	Public Building (Office)	Genetic Algorithm
	2020	Saikia Pranaynil, et al. (16)	Residential Building	Genetic Algorithm
	2021	Khan Nabeel Ahmed, Bhattacharjee Bishwajit(17)	Residential Building	NAGA-II
	2021	Khan Nabeel Ahmed, Bhattacharjee Bishwajit(18)	-	Genetic Algorithm

In recent years, scholars have gradually divided their research on building envelope structures into more specific areas. They have moved from studying the relationship between building envelope structures and architectural form to focusing on how building envelope structures can be adjusted based on their performance in sound, light, heat, and other aspects, as well as on the intelligent evolution of these structures. Abdel Rahman Wael Salah Mansour combined biomimetics with architecture, drawing inspiration from nature to propose a building design method based on a "modeling-simulation-optimization" framework. This method uses biomimetic algorithms such as genetic algorithms to optimize building envelope structures and minimize heat loss(15). Saikia Pranaynil et al. proposed a new genetic algorithm based on the summer temperatures in hot climates in India and used it to optimize building envelope structures for residential buildings in these conditions(16). In addition to focusing on the optimization of individual performance factors, many scholars have also chosen to consider multiple performance targets. For example, Khan Nabeel Ahmed et al. focused on tropical climates and used a multi-objective optimization method to study the simulation process of the mutual impact of insulation and noise insulation performance of building envelope structures. They developed a method to simultaneously optimize the thermal, visual, and acoustic performance of building structures, with the goal of minimizing energy consumption and improving the thermal, visual, and acoustic comfort of occupants(17,18).

Building Spatial Form

Similar to the optimization and generation of building envelope, the optimization research of spatial form in green buildings (Table 2) also takes individual building performances such as wind, light, and heat as driving factors, or integrates multiple performances to optimize building design.

Table 2. Typical Literature for Building Spatial Form Optimization.

Category		Year	Authors	Building Types	Platform	Algorithms
Single Objective Optimization	Wind Environment	2020	Nari Yoon , et al. (19)	Residential Building	Fluent + Python Grasshopper +EnergyPlus	CFD + Genetic Algorithm
	Light + Thermal	2020	Rouhollah Moosavi, Mohsen Golabi(20)	Public Building (Exhibition)	EnergyPlus	-
		2020	Sirine Taleb , et al. (21)	-	CPLEX + MATLAB	Penalty Successive Linear Programming (PSLP)
Multi-objective Optimization		2015	Kristoffer Negendahl, Toke Rammer Nielsen(22)	-	Radiance	Genetic Algorithm
		2020	Peiman Pilechiha, et al. (23)	Public Building (Office)	Rhino + Grasshopper	Pareto Bound + Weighted Sum Method + Hype

Category	Year	Authors	Building Types	Platform	Algorithms
	2016	Kyle Konis, et al. (24)	Public Building (Office)	Rhino + Grasshopper	Genetic + Annealing Algorithm
	2016	Longwei Zhang,et al. (25)	Public Building	Rhino + Grasshopper	Genetic Algorithm + Pareto Bound

Research on optimizing building form as a single driving factor using sunlight is relatively scarce. In most cases, daylighting and thermal performance are simultaneously considered as driving factors affecting building optimization. Rouhollah Moosavi et al. studied the impact of the form of exhibition buildings on solar absorption performance under cold, mountainous, hot, and dry climatic conditions, and identified the optimal forms corresponding to various climatic conditions(20). Sirine Taleb et al. used computational performance analysis with the CPLex and MATLAB software to propose a design optimization method that can maximize the reduction of solar exposure while maintaining the total required building area(21).

In the practical design and construction of green buildings, researchers aim to optimize various performance aspects such as wind, light, and heat simultaneously. However, these performance aspects often interact with and constrain each other, making it difficult to achieve optimal design through single-performance optimization. Therefore, in recent years, research on optimizing or generating building forms based on the integration of multiple performance aspects as driving factors, to achieve Pareto optimality, has gradually increased its share in the field of building performance optimization.

In 2015, Kristofer Negendahl et al. introduced the application of multi-objective genetic algorithms in comprehensive building design that considers various standards and proposed a rapid evaluation method suitable for the early stages of design(22). Peiman Pilechih et al. proposed a method for multi-objective analysis and optimization of office building window systems. Pareto optimality and weighted methods were used for multi-objective optimization to determine the best results that balance design requirements(23). Kyle Konis et al. optimized building geometry, orientation, window configuration, and other building parameters to improve lighting, solar control, and natural ventilation strategies, using a simulation-based parameterized modeling workflow based on PPOF(24). Li Ziwei et al. proposed a bi-directional early-stage performance optimization process for building design. Genetic algorithms were used to enable architects to perform rapid performance optimization in the early stages of design, simplifying the design process, starting from various performance indicators of buildings (25). Zhang Longwei et al. used multi-objective genetic algorithms to optimize the shape of buildings, ensuring the simultaneous achievement of three objectives: maximizing solar radiation gain, maximizing spatial efficiency, and minimizing form factors, reaching the Pareto optimal boundary(26). Sun Cheng et al. used an artificial neural network (ANN)-based multi-objective optimization design method to optimize the design of a public library in Changchun city, constructing a user-friendly integrated workflow that is more efficient and takes less time than a multi-objective optimization design process(27).

Building Cluster Relationships

In studying the relationships between building clusters (Table 3), the optimal layout of buildings is involved. This mainly includes two aspects: on one hand, independent of scale, centers on the configuration of building clusters, orientation optimization, and other self-contained architectural factors. On the other hand, primarily concentrates on the block scale, analyzing the interplay between buildings and surrounding streets, public spaces, environmental factors, and other interfaces to optimize design solutions.

Table 3. Typical Literature for Building Cluster Relationship Optimization.

Category	Year	Authors	Building Types	Platform	Algorithms
Among Buildings	2018	Nizam Onur Sönmez (28)	-	-	-
Between Building and Environment	2019	Zhifeng Wu, et al. (29)	ENVI - met	CFD	
	2020	Allen - Dumas M R, et al.(30)	Public Building	Python + EnergyPlus	-
	2019	Xiaodong Xu, et al. (31)	-	Rhino + Grasshopper	Genetic Algorithm
	2019	Ivana Bajsanski,et al. (32)		Ecotect, Rhino + Grasshopper	-

In terms of the relationships between buildings, research has mainly focused on the combination of green building and AI or other similar methods to automatically generate optimal layouts for building clusters. In 2018, Nizam Onur Sönmeze viewed the development of relevant methods for optimizing building design through AI in recent years, summarized how various optimization design methods have been applied in actual engineering and projects, and pointed out that existing AI design processes are relatively simple and lack the ability to solve complex problems(28).

In terms of building-environment relationship, the focus is primarily on deducing the relationship between the volume of the building and the elements of the environment, such as terrain and greenery. Zhifeng Wu et al. utilized the high-resolution ENVI-met model to study the quantity of buildings and trees in small-scale thermal environments to regulate the urban microclimate. They emphasized the practical significance of shading arrangements on the evolution of thermal environments in high-density cities(29). Melissa R. Allen-Dumas et al. focused on quantifying and analyzing the relationship between climate conditions, urban form, and energy use to assist in urban planning(30). Xu Xiaodong Xu et al. utilized genetic algorithms and Grasshopper tools to analyze the layout and configuration of urban open spaces in summer and winter, as well as their impact on urban microclimates. The goal was to optimize and improve the thermal comfort conditions of urban block open spaces(31). Ivana Bajsanski et al. utilized genetic algorithms and Grasshopper tools to analyze the impact of outdoor greenery on the microclimate of urban blocks. For example, determining the optimal distance between trees in the street to reduce the sunlight exposure on building façades and sidewalks, and providing guidance for more precise urban comfortable street block design(32). Alternatively, optimizing the location of trees in outdoor parking lots aimed to provide maximum shading for the parking lot while preserving the available parking space and the integrity of the parking shape(33).

Thanks to the rapid development of computer simulation technology and the continuous emergence and upgrade of related simulation software, performance-based design of green buildings has achieved significant progress. As a complex technical system involving multiple disciplines, performance-based building design has been the subject of diverse research by various scholars, but their approaches to optimizing design based on one or more driving factors share a common logic. Additionally, the software platforms, theoretical foundations, and design generation patterns relied upon by researchers in various cases can often be classified into several modes.

In terms of software platforms used for performance-based design, according to the statistics from the U.S. Department of Energy on building performance simulation tools, there are a total of 203 different types of performance simulation software, of which 68 are whole-building energy simulation software, accounting for 33% of the total. Among the software, researchers with a background in architecture tend to use performance simulation software such as Ladybug and Honeybee, as well as genetic algorithm analysis software such as Octopus and Galapagos, on the Rhinoceros 3D+ Grasshopper platform. In recent years, there has been a proliferation of green performance optimization designs at different levels of building scale, with numerous research results emerging in theoretical research, method analysis, and practical case applications.

However, before various building performance optimization methods can be widely applied in the field of green building and even form quantifiable standards, there are still some issues that need to be addressed for future development.

Firstly, current research mainly focuses on idealized building models and has less integration with actual building design projects. Whether it is the study of individual buildings or building clusters, current research on green building performance optimization design mainly focuses on residential and office buildings, with relatively less attention paid to other types. Among these, the study of the relationship between wind and solar radiation and the impact of building envelopes is the most researched. In fact, due to the fact that existing performance-based design is based on simulation calculation, it is difficult to achieve optimization for a wider range of building types with a single or small number of driving factors. The bottleneck of massive multi-objective optimization cannot be broken through with existing computing power. It is worth considering how to effectively apply performance optimization methods to complex building forms.

On the other hand, due to the differences in environmental factors in which buildings are located, existing optimization methods often can only be applied to a single issue, lacking a universal research method. This makes each research method only applicable to specific buildings. Digitalization, systemization, and multi-objective composite research methods will become important directions for future research.

1.2.3. A Brief History of AI

Prior to the 19th century, there existed a paradigm in physics known as the Newtonian Paradigm, which was based on Reductionism. Reductionism refers to a methodology that assumes any phenomenon can be understood by breaking it down into its constituent elements. Hence, the Newtonian Paradigm was used to describe mechanical motion, where the isolation of a building component from the structural system for the purpose of analyzing its behavior under loads and movement could be achieved through the method of isolation.

In the face of more complex research objects, such as thermal, optical, and electromagnetic phenomena, physicists have found limitations in the classical Newtonian Paradigm, which relies on reductionism to understand the workings of a phenomenon by breaking it down into its constituent elements. Consequently, they have proposed a distinctly different paradigm that considers the holistic and nonlinear aspects of such complex phenomena(34).

Of course, complex problems are not limited to physics; they exist across various disciplines. Examples include sociology's attempt to establish an optimal welfare system, chemical oscillating reactions, financial market forecasting, epigenetics in biology, and error control in engineering, among others. These problems exhibit dynamic, unpredictable, and multivariate characteristics, making traditional linear causality or reductionism inadequate to address them. As physicists have done, scholars in various fields are exploring more effective methodological tools to tackle these complex problems.

Systems Science and Cybernetics

Scientists have proposed various theories to study these difficult problems. Among them, revolutionary theories or concepts include systems theory, cybernetics, uniformity, emergence, fuzzy logic, mutation theory, chaos theory, fractal theory, and AI, among others. These theories collectively constitute complexity science and have gradually been applied to various disciplines. A simple and essential way to deeply understand complexity science is to trace its roots. Systems theory and cybernetics, which emerged in the 1940s and 1950s, are the starting points of complexity science, and their importance is self-evident (Figure 6) (35).

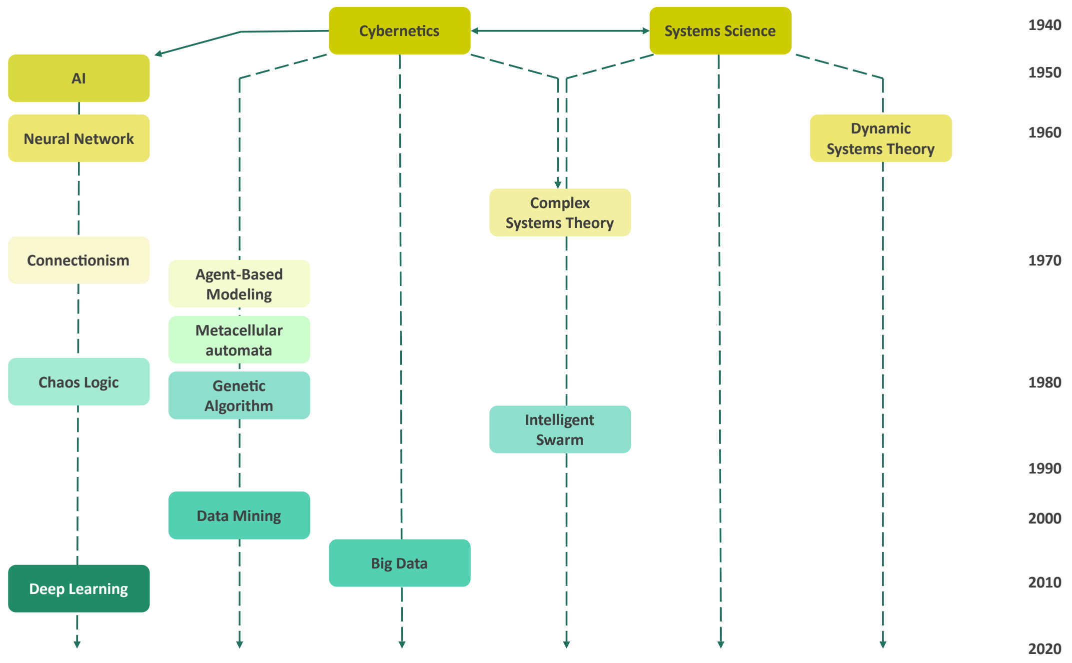


Figure 6. Complexity Science Development.

The concept of systems theory suggests that no matter how complex a phenomenon may be, researchers can always identify a number of systems that are inherent within it. These systems can not only be explained using concepts from their respective fields, but also described using a "universal" concept to reduce repetitive theoretical work across disciplines(36). However, the idea of attempting to unify knowledge across disciplines with a single framework has been controversial in subsequent developments. In particular, the issue of "uncertainty," an important concept in systems theory, has not been explored in depth. The consideration of only unidirectional causal relationships within a system may limit the ability to consider the overall impact of the system, resulting in a return to reductionism to some extent. To address this issue, Bertalanffy and other scholars sought to expand the potential of systems theory by establishing a feedback mechanism that would enable systems to exhibit adaptability, which led to the development of cybernetics(36).

Norbert Wiener, an American mathematician and philosopher, published the foundational work of what came to be known as cybernetics in 1948, titled "Cybernetics: Or Control and Communication in the Animal and the Machine." Wiener proposed that the behavior of biological or mechanical systems is purposeful, and to achieve their goals. These systems rely on information exchange with other systems or the external environment, and employ feedback mechanisms for self-maintenance, self-adaptation, and self-organization (Figure 7) (37).

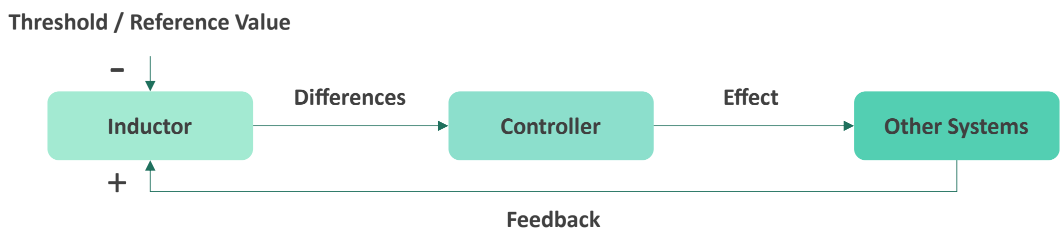


Figure 7. Cybernetic Loops with Feedback Mechanisms.

The emergence of systems theory and cybernetics in the post-World War II era cannot be overlooked as significant scientific movements. The rapid economic growth and optimistic social atmosphere after the war led the public to believe that science would lead to social liberation. The mass production and consumption patterns attempted to give architecture flexibility to meet diverse lifestyles and consumer needs. At the same time, there was a paradigm shift happening in various fields from science to humanities, from military to art. People began accepting new theories such as information theory, general systems theory, cybernetics, and emerging concepts like early AI, and architecture was no exception.

Early Limitations of Complex Science

In the context of systems theory and cybernetics, architects had a theoretical foundation to understand and respond to the complex reality. The avant-garde architects of that time believed that architectural space is a combination of ordered spaces that can adapt to changes in the external environment. Their explorations often resulted in visually identifiable, systematic spatial structures. Examples include the white, homogenous, gridded monument of "The Continuous Monument" by SuperStudio, and the multi-level networked space structure of "New Babylon" by Constant Nieuwenhuys, supported entirely by columns. These ordered physical spaces reflected the presence of rules or orders that "control" their combinations.

The collision between architects and computers in the early days can be said to have started with a relatively simple logical process. That is, by defining clear logic, computers were made to perform calculations. At that time, based on this programming method, some people used iterative algorithms to generate hospital floor plans and optimized the design based on the shortest walking route for patients(38). Some tried to use programs to find a reasonable basis for determining the shape of multi-story buildings and optimizing the location layout of various functional spaces. Others used probability theories such as graph theory to process collected data and design algorithms, ultimately resulting in the lowest cost solution(39).

As exploration of computer use deepened in the field of architecture, architects realized that they were facing extremely high levels of complexity and uncertainty. Even explicit programming was difficult to cope with and manage. Therefore, the nascent field of AI quickly entered the architects' field of vision. Early pioneers began attempting to apply the concepts and intelligent algorithms of AI to architecture to handle this complexity.

The Emergence and Winter of AI

Before the concept of AI was officially introduced, the primary issue was how to distinguish it from human intelligence. The first to propose criteria for judgment was computer scientist Alan Turing. The Turing Test, which he proposed in 1950, remains the gold standard for determining whether a machine exhibits intelligence equivalent to or indistinguishable from that of a human(40).

Not long after the Turing Test was proposed, the term "artificial intelligence" was introduced to define and describe these human-like intelligent systems. It is generally believed that the term was officially coined, and the research direction of this field was established at the Dartmouth Conference in 1956(41). In fact, about a year before the conference was held, on August 31, 1955, the term "AI" had already appeared in a proposal for a seminar(42). The authors of the proposal included prominent figures in the field at the time, such as John McCarthy from Dartmouth College, Marvin Minsky from Harvard University, Nathaniel Rochester from IBM, and Claude Shannon from Bell Labs.

At the time, their research on AI was based primarily on an assumption that all aspects of human learning or any feature of human intelligence could be precisely described, so that machines could be created to simulate that learning or intelligence. This proposal outlined the general outline of the field of AI. That is, attempting to find ways to enable computers to understand, find features and patterns from data, and generate corresponding concepts, enabling computers to abstract and conceptualize to solve computational problems that only humans can handle, such as proving mathematical theorems, finding the shortest path between two places, etc., or learning from failures and improving performance for self-improvement. In other words, making machines behave "intelligently" like humans.

Following the Dartmouth Conference, the first wave of research in AI emerged. Several years later, the attendees and related scholars began developing systems such as the Logic Theorist, a program capable of automatically proving theorems, the General Problem Solver, and the Samuel Checkers-playing Program, using methods guided by logical reasoning, heuristics, and other theoretical approaches. In the mid-1960s, the US Department of Defense provided substantial funding for AI research and established laboratories worldwide. At the time, the founders of AI generally held an optimistic outlook for the future. Herbert Simon prophesied that machines would be able to perform any task that humans could do within twenty years(43). Marvin Minsky concurred, stating that the issue of creating AI would be substantially resolved within a generation(44).

However, throughout history, these aforementioned scholars may have been overly optimistic in their expectations for the development of AI. By the mid to late 1970s, due to the fact that most of the achievements in AI research remained confined to the laboratory and failed to meet the high expectations of the public in terms of application, the development of AI fell into the first winter. This stagnation also to some extent affected the early exploration of generative design through computers in architecture.

Prior to the winter of AI development, explorers in architecture, such as the Architecture Machine Group at MIT, attempted to leverage AI concepts to expand the possibilities in architecture. Recognizing the limitations of computers and early AI technologies at the time, some architects turned to continued theoretical deliberation, resulting in research achievements such as "Pattern Language"(45) and "Shape Grammar"(46).

As computers became more widely used in commercial applications, architecture began to embrace digitization again in various aspects. Subsequently, significant advancements in computer performance, software technology, and human-computer interaction technology paved the way for the development of generative design. The trend of generating architectural design through computers was revived, and performance-based design, including parametric design, flourished.

However, as described before in this section, current performance-based design achieved through algorithms is still very similar to early explicit programming, requiring clear and explicit definition of parameters and their relationships using embedded. These operations must be completed through predefined programming syntax. Due to the inherently complex nature of the design process, it is sometimes difficult to fully express the involved parameters through code, which can make it difficult to deal with complex situations in design. Such as abstract parameter definitions, complex relationship expressions between parameters, and the search for design variables.

After more than half a century of development, AI has become a topic of frequent discussion, but its integration with practical application scenarios is not yet clear. At the beginning of the 21st century, with the widespread application of big data, storage, and computing power steadily improved, machine learning (especially deep learning) algorithms, have been fully utilized. This has led to a comprehensive explosion of images, texts, transactions, and mapping data. In recent years, AI has triggered a profound technological revolution worldwide. The combination of continuously expanding storage and computing power, sudden surges of data, and existing algorithms allows us to carry out timely and efficient storage and processing. In the practice and scientific research of architecture and urban design, the involvement of AI may give rise to various new possibilities.

The technological innovations of internal combustion engines and electricity have been the fundamental driving force of economic growth over the past 250 years, while AI is set to become one of the most important general-purpose technologies of our time. In the next several years, almost every industry will face opportunities and challenges brought about by the revolutionary impact of machine learning technology on their field.

1.2.4. A Surge Before the Next Paradigm of Architectural design

In the face of growing data and increasingly complex design processes, the major challenge and problem that the current field of architecture and urban design faces is the multidimensional considerations in design decision-making, as well as the increasingly complex and difficult to control design processes. The emergence of AI and related computer-aided technologies have provided guidance to both architects and researchers in exploring the unknown areas and hidden logic of urban and spatial sciences, using the power of computers.

Generally, the client's needs are always ambiguous. In traditional architectural design, the architect gradually clarifies the real requirements of the client in the process of constantly revising the design. Only after that, the cycle of "simulation-optimization-re-simulation" could be carried out. After determining the preliminary design, the project moves on to the production-oriented detailed design phase. Although performance-based architectural design tools speed up the optimization process to a certain extent, the establishment of preliminary solutions is still costly. Architects are passively focused on how to delicately represent the design solution to try out the client's requirements. This process of solving unclearly defined and complex design issues remains limited by the knowledge and capabilities of individual architects or teams. The architectural design paradigm has not fundamentally changed.

The emergence of AI has opened up new possibilities for the architect and client. The architect is given the opportunity to focus on defining design requirements with the client, providing creative design inspiration, and enabling a direct "inspiration-design solution" transition. Ideally, with a simple selection and adjustment, AI can transform multiple design directions into implementable design solutions in a single day (Figure 8). At the same time, the knowledge space for solving complex problems is no longer limited to the individual architect, but rather the aggregate of the architect and the model (Figure 9).

We should note that AI technology is not just a tool, but a set of "system paradigms" behind it. This paradigm includes new workflows, categories, objects, as well as logic, judgments, and indicators in design thinking. The most important thing, obviously, is the redefinition of the issues that design deals with and design itself.

The new AI technologies will effectively provide new paradigms, free the imagination of designers, bring multidimensional information interaction and diverse designs from a larger scope and broader context, and inject new vitality into traditional design models.

To speak with prudence, it remains difficult to predict the future of architecture and urban studies in an AI era that has not yet fully arrived. However, among the possibilities, which will become a reality in the future depends on the efforts and choices made by the industry. As Cixin Liu has mentioned when describing the age of AI, "Regardless, it is an enticing age towards which we are heading."

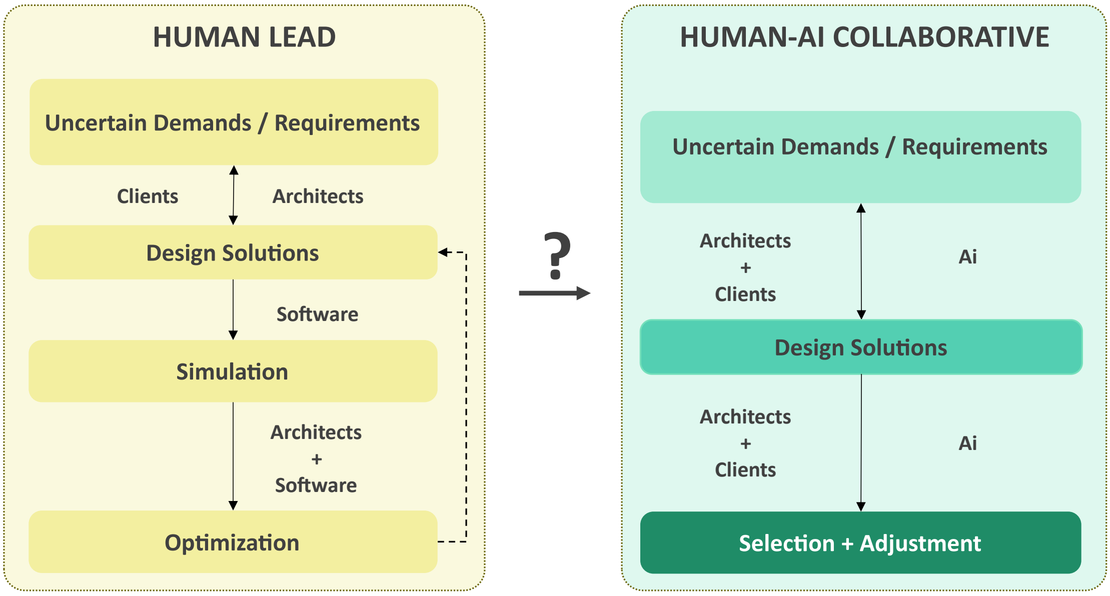


Figure 8. Architectural design Paradigm Transformation.

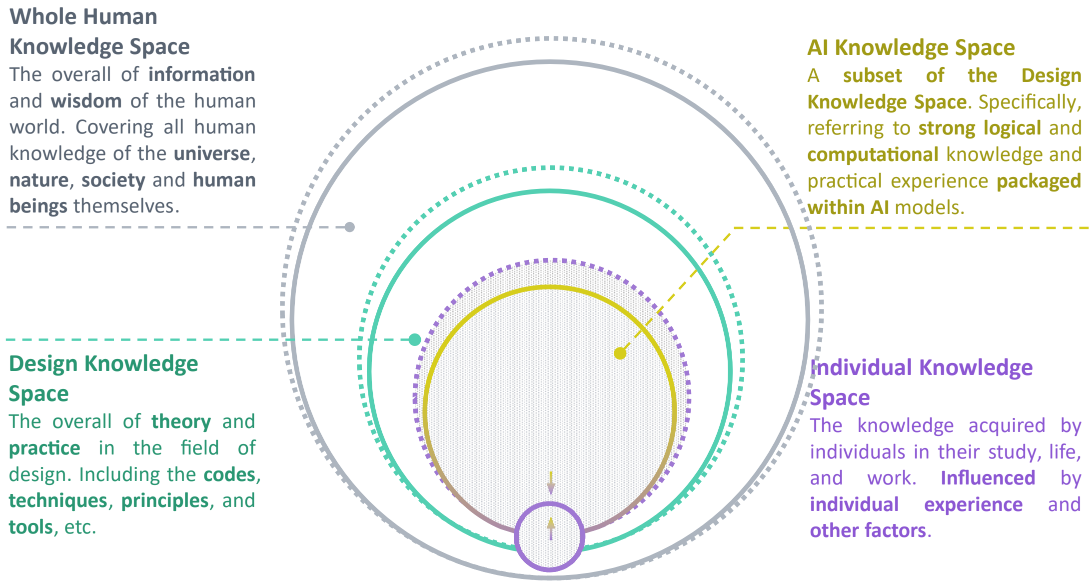


Figure 9. A Leap in Design Capabilities with AI Collaboration.

1.3. Research Purpose

1.3.1. Research Motivation

As previously mentioned, the enormous energy consumption in the B&C industry, combined with the significant development of performance-based design and AI, has led to the exploration of innovative integration between the disciplines of architecture and AI. The fundamental motivation of this study is to study a deep learning-based approach to adapt the human-ai collaborative design paradigm.

1.3.2. Research Objective

Based on the initial issues mentioned above, the ultimate goal is to leave the "strong logical" and "strong computational" parts to AI, unleashing the creativity of architects and improving the efficiency and performance of architectural design.

With this ultimate goal, this research expects to select appropriate models to be trained and tuned through extensive observation of AI technology, so that they can have the ability to generate plan and façade of low-rise residential buildings with improved performance. At the same time, the human-AI collaborative design process will be explored in this process.

With such objectives in mind, this research will select appropriate neural network models based on the results of literature review. To find the research gaps and potential strategies of them. Based on that, the research will attempt to propose a deep learning-based model for generating design solutions for low-rise residential buildings. Furthermore, appropriate data augmentation, tuning and iterative training may need to be conducted and evaluated.

1.4. Research Framework

As mentioned in section Preface, how can AI technology give wings to sustainable architectural design? The topic is full of challenges and opportunities.

First of all, architects should have a deep understanding of AI technology and master its fundamental principles and application methods. In addition, they should also have a broad knowledge background, including knowledge in the fields of building physics, energy management, building materials and building energy efficiency technologies. This will enable architects to fully understand the energy consumption and performance of buildings and understand the application of AI technologies in these areas.

Secondary, architects need to work closely with technical experts to develop AI algorithms and software that enable sustainable building design. In this process, architects can provide their expertise and experience in sustainable building design, while technical experts can help architects translate this knowledge into actionable algorithms and software.

Finally, architects should keep learning and innovating. In the context of the rapid development of AI technology, architects should maintain an open mind and constantly adopt new technologies and methods. At the same time, they should also continue to innovate and explore new sustainable architectural design ideas and methods to meet the changing market demand and social development requirements.

To address the above research objectives, it is possible to formulate the specific operational research stages and the research methods that can be implemented at different stages to elucidate the solutions to the research issues.

Approaches Toolbox - Prior to the new design paradigm, the implementation of AI in the B&C industry has emerged in a sporadic manner. Undoubtedly, scholars are exploring different application domains to varying degrees. In order to achieve the generation of energy efficient residential building designs, the following questions need to be answered first.

- Which AI technologies are employed in which research fields or orientations?
- Within the same field, are there any advantages or disadvantages in the application of the technologies?
- What are the potentials or possibilities of AI technology implementation in terms of sustainable building design?

Approach Construction - The answers to the above questions will provide the methodological basis and architectural reference for the next research. Once be clarified, the subsequent issue will be the construction of the neural network.

- What kind of samples should be employed for training?
- How will the training results be verified or evaluated?
- If the training results do not meet the requirements of the study, how can they be improved or modified?

Approach Validation - Are the generated residential building design solutions with energy-effective performance?

- What kind of simulation tools are used for validation?
- Which simulation indicators can be assigned to verify the validity of the approach?

Based on the above research questions and the iterative methodological research strategy, the research framework of this thesis is formulated as follows (Figure 10).

Chapter 1 (i.e., this chapter) elaborates the research background and research purposes and presents the research motivation and objectives by introducing the current status of energy consumption in the B&C industry, resolving the development of performance-based design, and the interaction and development of AI and architectural design. The research framework is also organized.

Chapter 2 will be a systematic review of recent literature and data analysis. The aim is to sort out the hot spots of AI technology applications in different research fields through systematic analysis of research trends combined with cross-comparative generalization. In other words, the answers to the aforementioned " Approaches Toolbox" questions will be answered in this chapter. At the same time, the research gaps are summarized to guide the next stages.

Chapter 3 is the methodological chapter. This chapter will present the research strategies to cope with the above research gaps. It will also briefly address the research methods adopted under these strategies.

Chapter 4 to Chapter 7will present the implementation of the above strategies in detail. This includes enhancing the performance of model generation results through empowering of samples, improving model generation capabilities through data augmentation and generator replacement, and conducting an empirical study of human-AI collaborative design processes and results through practical projects.

Chapter 8, which concludes, will summarize the above overall research from both theoretical and practical aspects. Meanwhile, the imagination of future advancement will try to be developed.

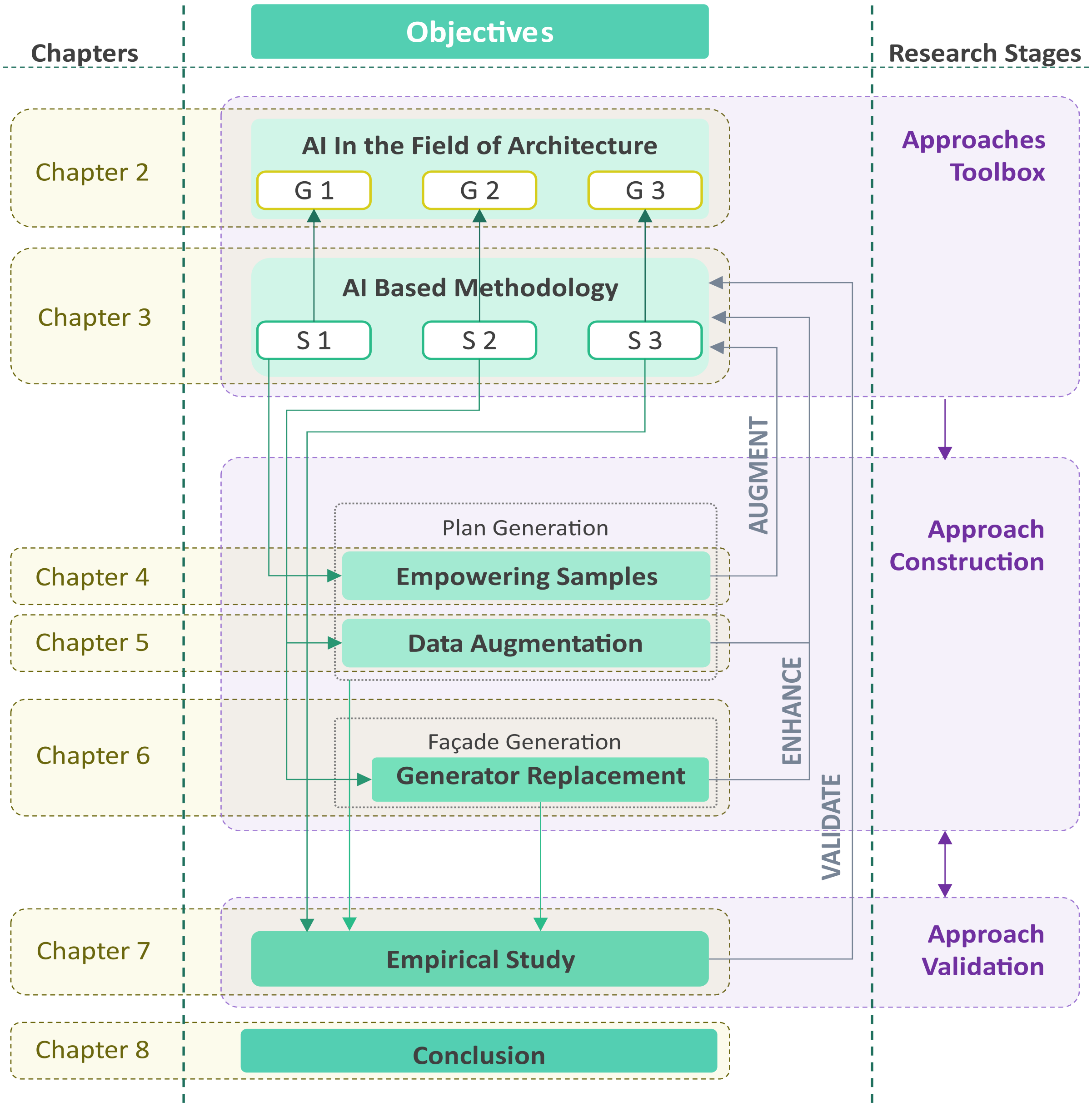


Figure 10. Research Framework.

Chapter 2. AI In the Field of Architecture

2.1. Introduction

As mentioned before, the building industry, the largest industry in the world(47), has the lowest level of technological innovation and digitalization(48). At the same time, the diverse internal and external complexity of the design, construction, operation and maintenance of "buildings", and even their demolition, poses an increasing challenge(49).

For more than half a century, architects have been pursuing the development of AI techniques to find the "optimal solution" to address the challenges. In this process, five tribes have emerged, namely Symbolism, Bayesian, Analogy, evolutionary, and Connectionist(50). However, the question of how AI can effectively help architects solve which problems remains unclear.

Regarding the Approaches Toolbox mentioned in section 1.4 above this research stage will first perform a knowledge mapping analysis of current relevant studies to identify the clusters of them. Subsequently, a more in-depth analysis of these studies will be conducted to obtain the relevance of algorithms to the research task and to predict trends in upcoming research. This will establish the theoretical basis for conducting the optimal neural network to be used in the next stage of this research.

2.2. Analysis Methods

Knowledge mapping is generally used to collect, organize, and summarize literature by constructing relationships and visualizing "network data" for scientific knowledge analysis. The knowledge mapping tool used in this stage is the Java-based VOSviewer(51) Leiden University, which can be used to build networks of scientific publications, researchers, research organizations, countries, keywords, and terms. The keywords of an article could highly summarize the research scope, research methods, and content of the article, etc., while the interconnection between keywords constitute the research ontology of the field. Therefore, this research stage uses bibliometric methods for keyword network co-occurrence based on VOSviewer to cluster the research hotspots of AI techniques applied to the field of architecture （Figure 11）.

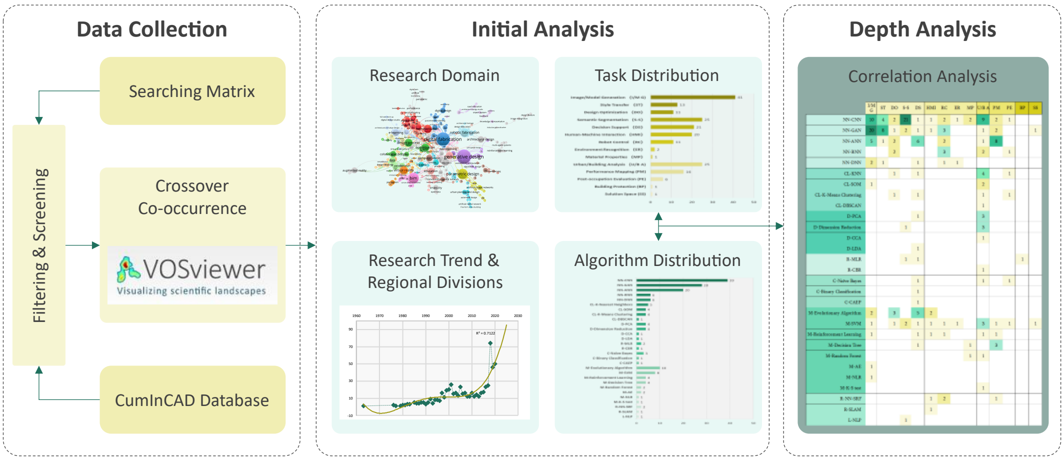


Figure 11. Literature Analysis Framework.

For the study of the relevance of algorithms to research tasks, this stage uses a simplified form of panel data for statistics. The use of this method allows a more intuitive expression of the relevance strength. At the same time, the future research trends can be roughly predicted when comparing the correlations with the historical mapping of keywords.

2.3. Data Acquisition

The data in this stage were obtained from the CumInCAD database, a cumulative index of publications about computer aided architectural design designed and created by Prof. Bob Martens of the Vienna University of Technology, and Prof. Ziga Turk of the University of Ljubljana in 1998. It contains bibliographic information of important international journals and conferences in the field of digital architecture, such as ACADIA, ASCAAD, CAADRIA, eCAADe, SiGraDi, CAAD futures, DDSS and others. Consequently, the search results collected from CumInCAD are quite authoritative in reflecting the overall research and development trend of digital architecture.

<table>
<tr><th rowspan="2">Base Keyword</th><th rowspan="2">Searching Focus</th><th colspan="3">Additional Searching Criteria</th></tr>
<tr><th>title</th><th>keywords</th><th>summary</th></tr>
<tr><td rowspan="17">machine learning</td><td rowspan="3">the broader terms</td><td colspan="3">data</td></tr>
<tr><td colspan="3">feature</td></tr>
<tr><td colspan="3">training</td></tr>
<tr><td>Result Naming</td><td>ML-TT-01</td><td>ML-KW-01</td><td>ML-SM-01</td></tr>
<tr><td rowspan="4">the main strategies</td><td colspan="3">regression</td></tr>
<tr><td colspan="3">classification</td></tr>
<tr><td colspan="3">clustering</td></tr>
<tr><td colspan="3">PCA</td></tr>
<tr><td>Result Naming</td><td>ML-TT-02</td><td>ML-KW-02</td><td>ML-SM-02</td></tr>
<tr><td rowspan="5">the specific approaches</td><td colspan="3">genetic</td></tr>
<tr><td colspan="3">evolutionary</td></tr>
<tr><td colspan="3">fitness</td></tr>
<tr><td colspan="3">K-</td></tr>
<tr><td colspan="3">neural network</td></tr>
<tr><td>Result Naming</td><td>ML-TT-03</td><td>ML-KW-03</td><td>ML-SM-03</td></tr>
</table>

Figure 12. Literature Searching Strategy Matrix.

Since "AI" is a widely used term, it tends to cause an explosion of data search results. We need to control the precision of the results by setting reasonable search terms (Figure 12).

In this stage, the following search criteria in CumInCAD was set search for "machine learning"(ML) in the advanced search, and the additional criteria are matrix fuzzy search for title, keywords, and summary in three levels. The first level was for the broader terms involved in ML: data, feature, and training, and the second level was for the main strategies including:

regression, classification, clustering, and data dimension reduction (using PCA instead). The third level was the more specific approaches in ML: genetic, evolutionary, fitness, K- (fuzzy for "kernel" related algorithms), and neural network. The search was conducted on August 1, 2021, and a total of 621 eligible articles were found, the earliest of which appeared in 1963.

2.4. Statistical Analysis

2.4.1. Research Domain

The keywords of the 621 articles were identified and processed and a total of 1236 keywords were identified. Table 4 lists 10 keywords with the highest frequency and their total link strength (occurrences/total link strength) excluding common words such as: machine learning (75/265), AI (30/110), deep learning (18/64), architecture (16/72), neural networks (12/46), learning (12/48), design (11/55), ai (9/37), design methods (9/36). It can be seen that "generative design" and "digital fabrication" have the highest total link strength and the highest relevance to other articles.

Table 4. Top 10 Keywords with Highest Occurrences.

Keyword	Occurrences	Total Link Strength
generative design	23	93
digital fabrication	21	85
BIM	15	56
parametric design	14	49
robotic fabrication	11	53
representation	10	55
virtual reality	10	39
optimization	9	38
design process	9	36
information processing	9	36

VOSviewer identifies keyword as "item" when co-occurring in the network, which are represented by circles, and the larger the weight, the larger the size, the higher importance. The connection between keywords is identified as "link", and the number of links for each item indicates the number of other items associated with it. These items and links form the keywords co-occurrence network. To form clearer clusters, all 1236 keywords were co-occurred in the network in this stage, and there were 1236 items and 3449 links in the co-occurrence network. The items with high relevance in the network formed 132 clusters in this network (Figure 13).

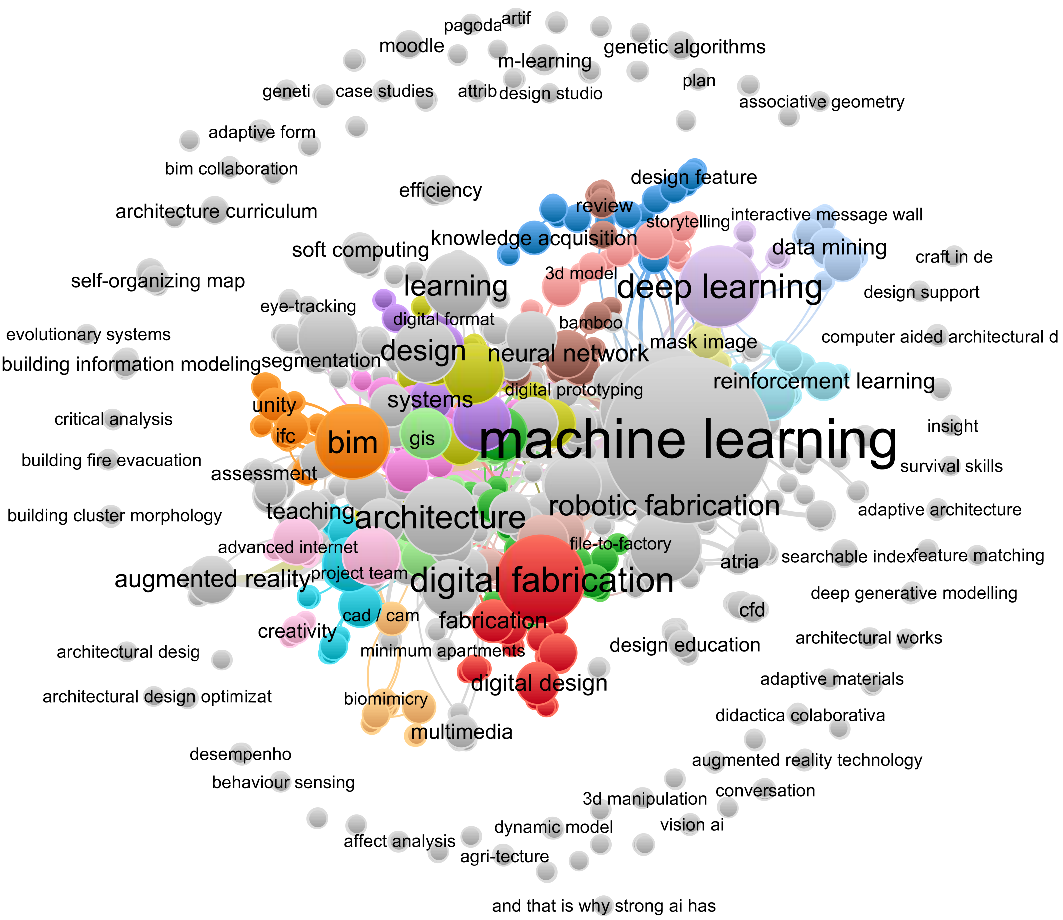


Figure 13. Co-occurred Network Visualization (Full Keywords).

Further, the common words listed in the previous were removed and 790 interrelated items were retained for knowledge mapping construction again (Figure 14). The 27 clusters obtained were sorted by the number of items, and the top 10 cluster central word and high frequency words were collated (Table 5).

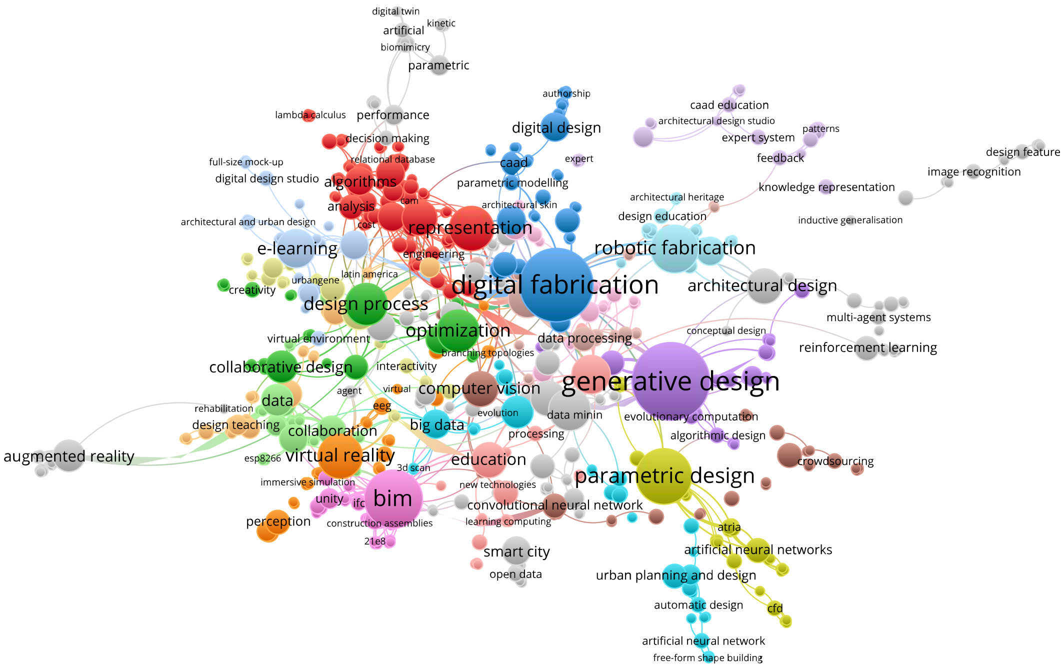


Figure 14. Co-occurred Network Visualization (Removed Common Words).

Table 5. Top 10 Major Keyword Clusters.

Color	Central Word	Frequent Items	Number of Items
Red	representation	cad, systems, algorithms, database, knowledge, user interface, computer graphic	81
Green	design process	optimization, programming, collaborative design, internet of things	44
Blue	digital fabrication	material, generative, human-computer interaction, construction, caad, digital design, fabrication	43
Yellow	parametric design	ANN, design methodology, complex geometry, cfd, daylight, building energy, cim	39
Purple	generative design	structural design, form finding, data-driven design, MOO, evolutionary, façade design,	38

Color	Central Word	Frequent Items	Number of Items
Nattier	big data	data visualization, design trends, design history, data analysis, urban planning and design, semantic segmentation, GAN, ANN	37
Orange	virtual reality	interaction human-machine, perception, soft computing, eye tracking, wearable design, EEG, signal processing, style-transfer	35
Brown	computer vision	CNN, photogrammetry, satellite image, drone, crowdsourcing, human computer interaction, recognition and segmentation, remote sensing	34
Pink	bim	depth image, early design stages, unity, parametric construction detail, bim-vr integration	33
Incarnadine	computational design	education, urban planning, tasK-based approach, urban analytics,	32

2.4.2. Research Trends and Regional Divisions

As shown in Figure 15, the number of articles related to ML published before 2016 is relatively small. 2016-2021 shows a clear upward trend, among which the CAADRIA conference held in Beijing in 2018 had a large impact on the values of that year. It should be noted that the number of articles in 2021 was not counted here to eliminate the effect on the regression.

Comparing Figure 14 and Figure 16 could conclude that researchers began to explore uncertainty in architecture with system theory, cybernetics, and complexity science as the main entry point in the early days. Later, with the development of technology and tools, the study of form finding and building performance became a hot spot for research in turn. In recent years, the state-of-art algorithms of deep learning have been broken through and gradually applied to the research fields of design process, fabrication process and urban planning, showing a blossoming trend.

In terms of annual publication volume, the US, UK, and Australia are involved from early basic research to current innovative research. Developing countries, represented by China and

Brazil, have emerged in the last five years and are gradually on par with most European countries (Figure 17). In terms of cumulative publications, the US tops the list with 158 articles. China has the second highest number of articles with 58, while the UK is in third place with 56 articles.

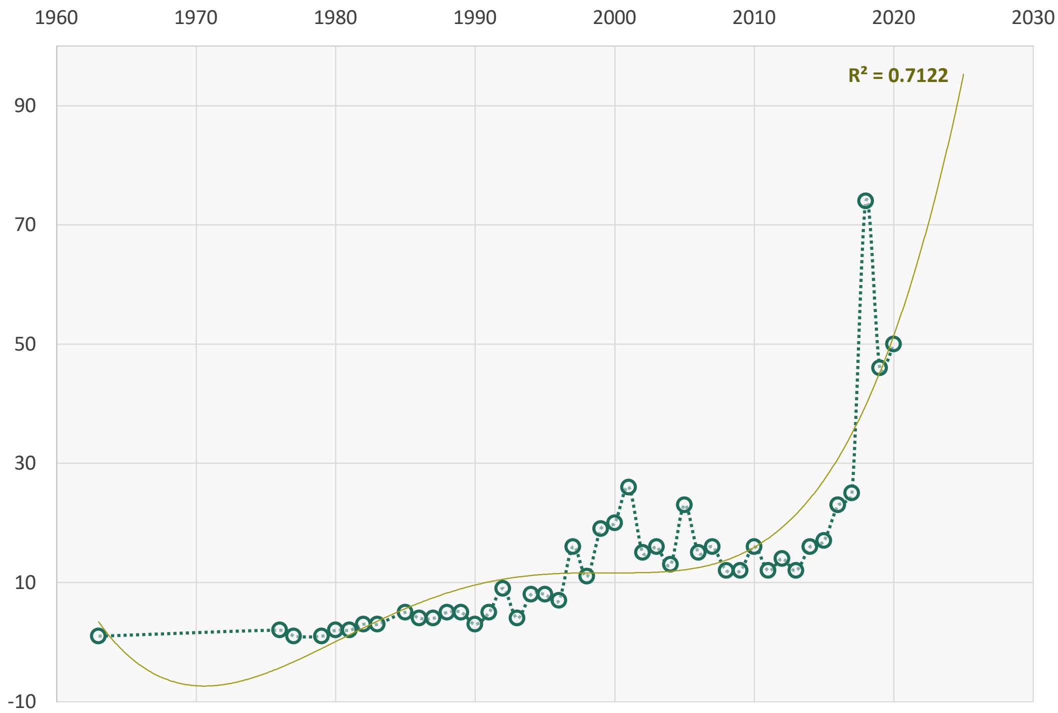


Figure 15. Number And Trend of The Related Articles Published (1963-2020).

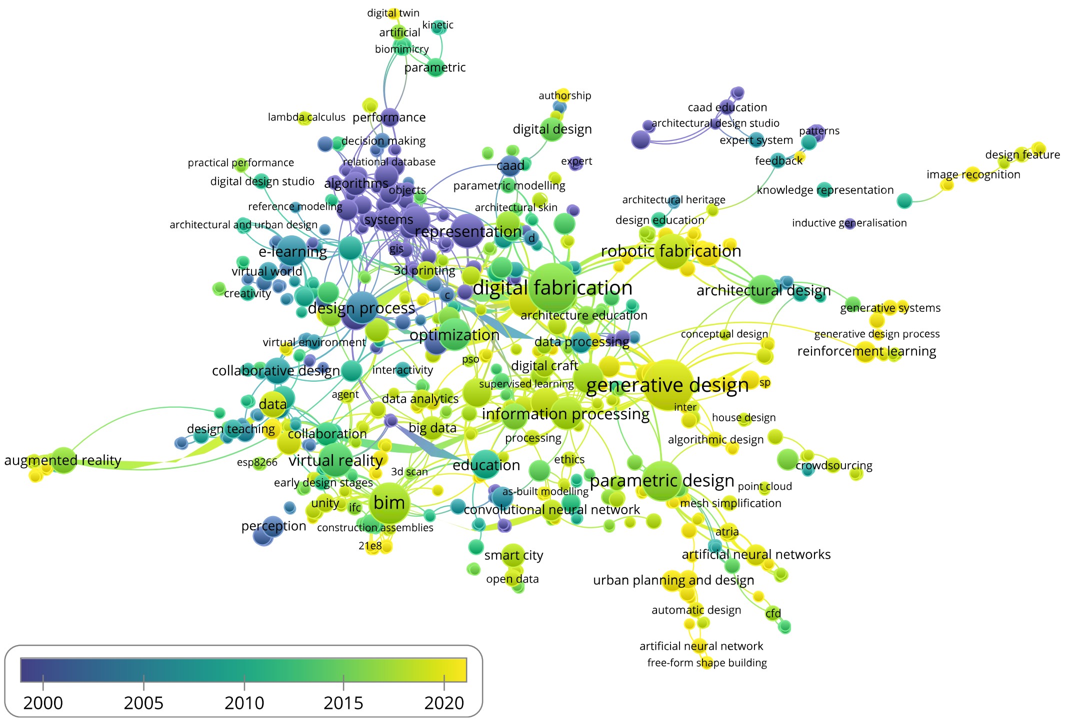


Figure 16. Overlay Network Visualization by Year (Common Keywords Unselected).

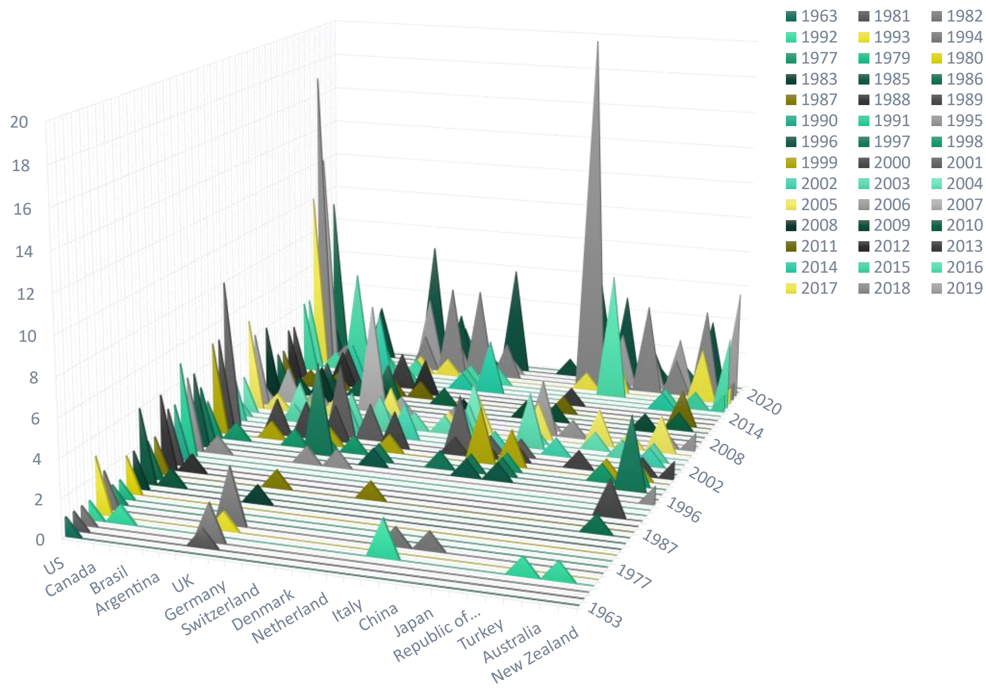


Figure 17. Annual Volume of Articles by Country (Accumulate More Than 10 Articles).

The knowledge mapping was compared and analyzed again after removing the items "machine learning" and "architecture". The analysis shows that:

1) North American countries (92% in the US) mainly focus on basic algorithms and design methods research, and the mapping density is very high, and the research is much earlier (Figure 18).

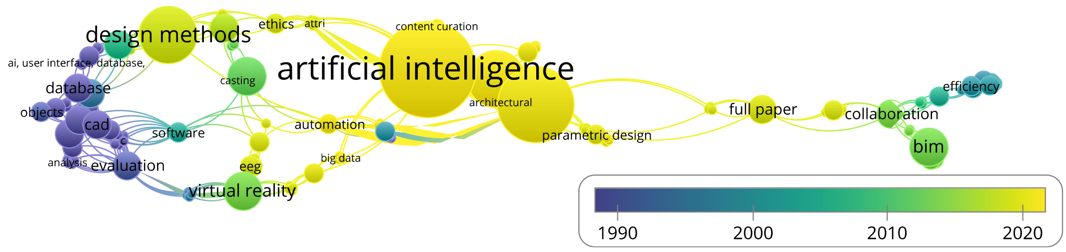


Figure 18. Overlay Network Visualization by Region & Year (North America).

2) South American countries (52% in Brazil, 23% in Argentina, 8% in Chile and Venezuela each) mainly focus on teaching research of parametric design and BIM. The mapping density is low, showing the possibility that the research is not systematic enough, and the research time starts later (Figure 19).

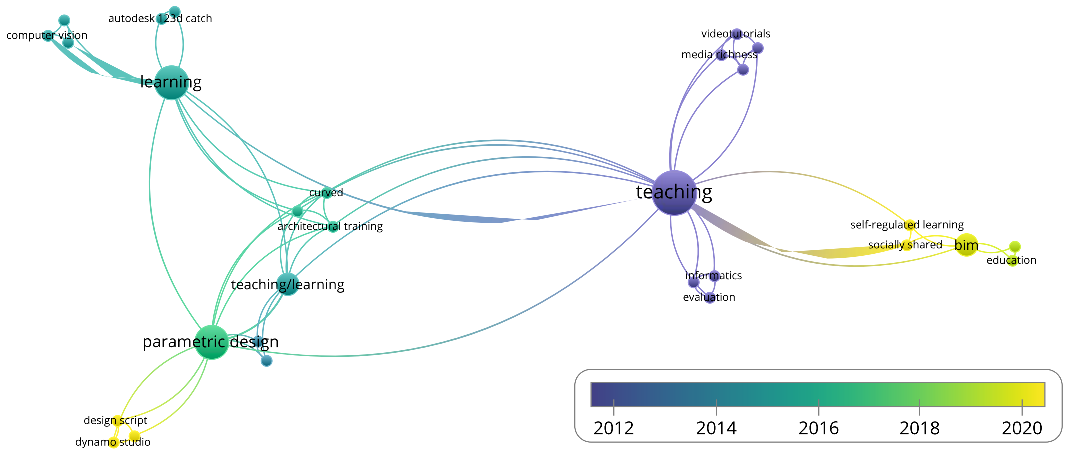


Figure 19. Overlay Network Visualization by Region & Year (South America).

3) European countries (29% in UK, 13% in Germany, 10% in Switzerland and Denmark each, 7% in Netherlands and Italy each, 5% in Austria and Spain each) have made great number of achievements in digital process, digital fabrication, generative design and BIM, as well as basic algorithms and AI. But the research time is about decade later than North America (Figure 20).

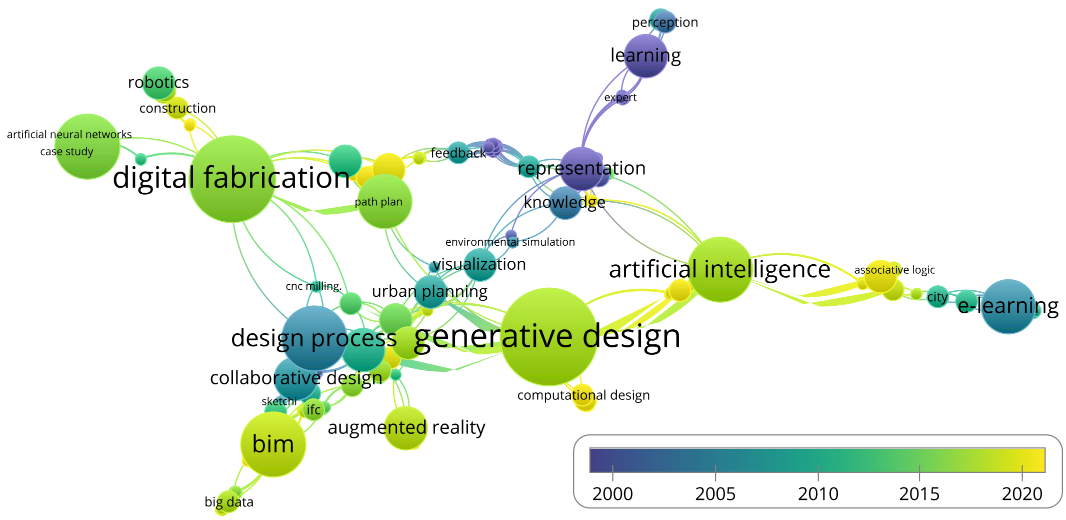


Figure 20. Overlay Network Visualization by Region & Year (Europe).

4) Asia and Africa countries (42% in China, 13% in Japan, 11% in Republic of Korea and Turkey each, 7% in Singapore) started the research the latest with weaker foundation. However, the recent number of research is extremely huge and highly focused on the cutting-edge deep learning and AI (Figure 21).

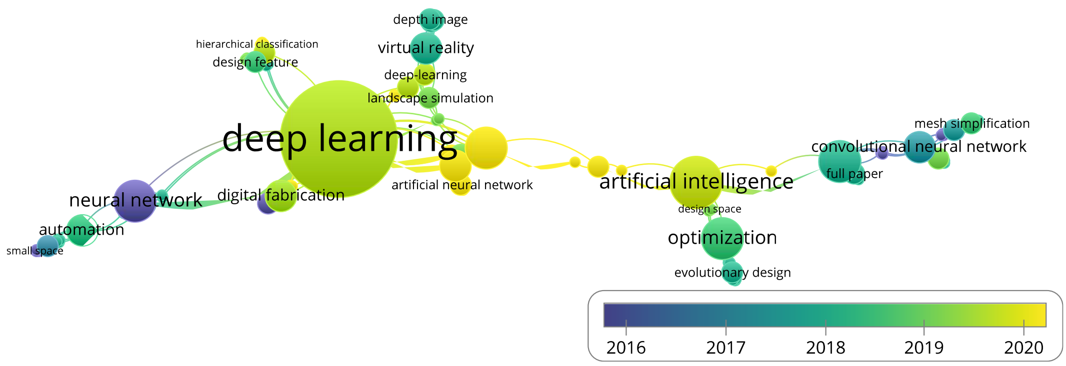


Figure 21. Overlay Network Visualization by Region & Year (Asia + Africa).

5) Oceania countries (88% in Australia) also started research quite early. Although the number is small but concentrated in digital fabrication and AI, showing a strong research aggregation (Figure 22).

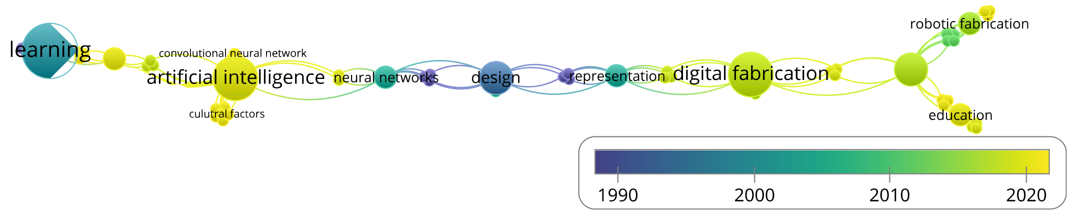


Figure 22. Overlay Network Visualization by Region & Year (Oceania).

2.4.3. Task Distribution

To analyze the recent research results more clearly, the 240 articles from 2016-2021 were selected to be classified according to their research objectives, which can be divided into generative design, digital fabrication, deep image (in a general sense of image-based research, rather than in the traditional sense of the concept), regression & prediction, classification, building/environmental performance, education, review, and others as shown on Figure 23.

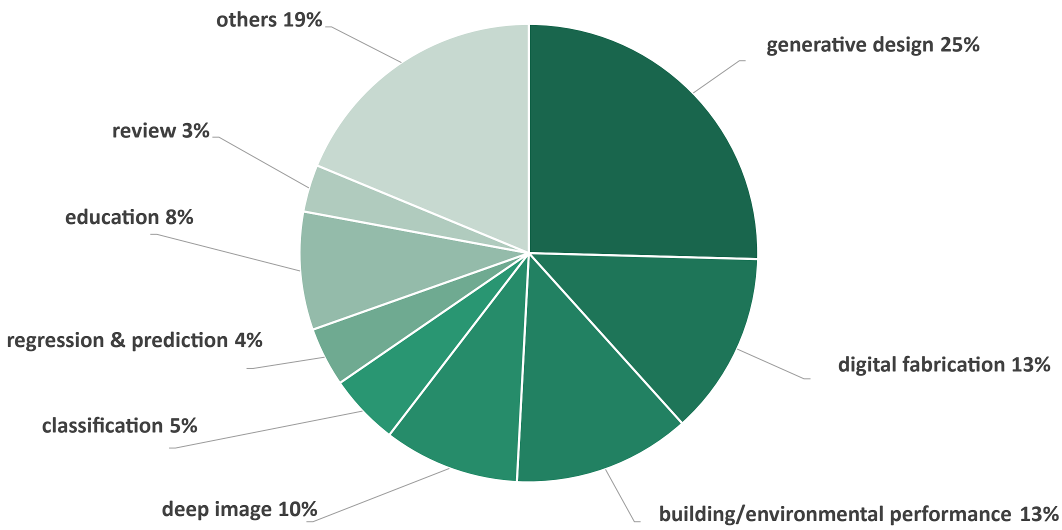


Figure 23. Distribution of Research Objectives Related to ML (since 2016).

Further analysis of the first 6 categories of studies revealed that, despite the different research objectives, the roles of algorithms overlap to varying degrees and that multiple algorithms are involved in different stages of tasks of the same study. Therefore, based on the 14 research tasks summarized, the algorithms in the 167 articles involved in the above classification were again analyzed in detail. The objectives of the tasks are obtained in Figure 24.

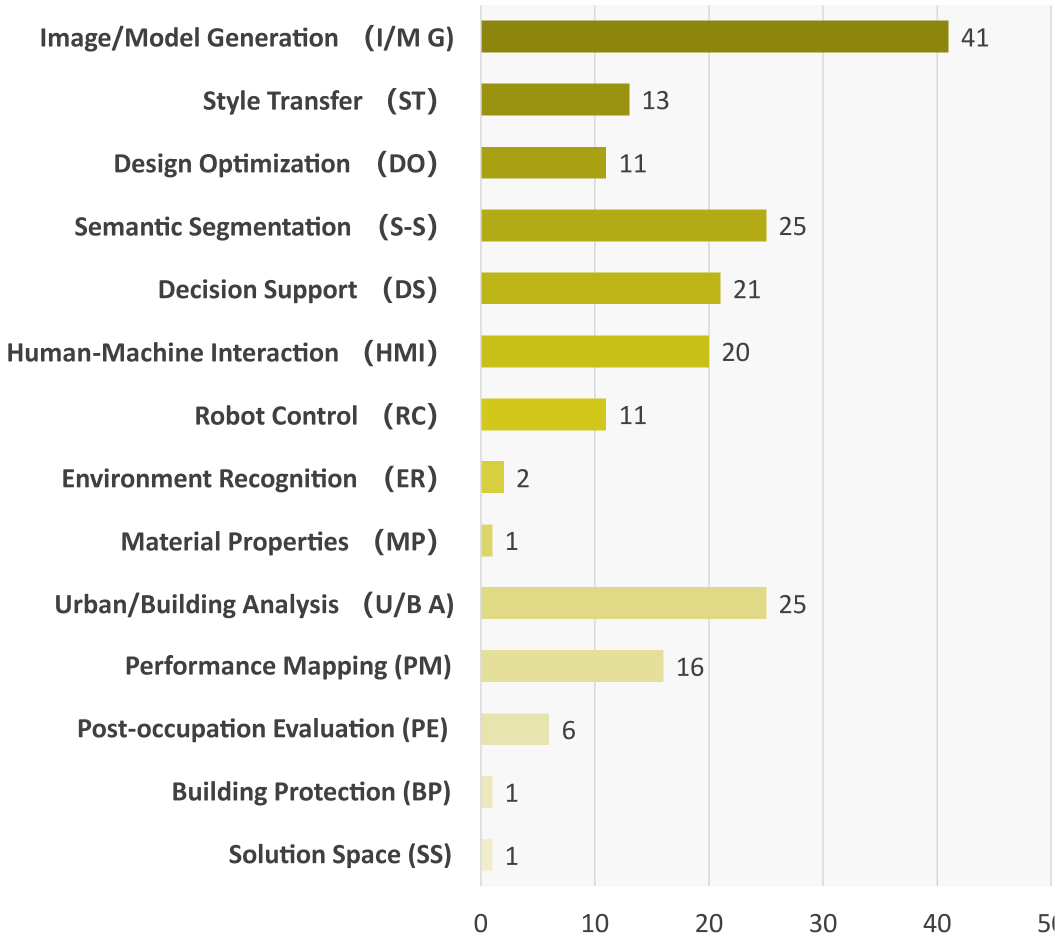


Figure 24. Distribution of Research Tasks Related to ML (since 2016).

2.4.4. Algorithm Distribution

Figure 25 shows the number of various types of neural networks and other ML algorithms used in the above articles. It can be roughly divided into 8 categories: neural network, clustering, dimension reduction, regression, classification, multipurpose, robotics and language processing. The results show that 99 studies used neural networks, with the most studies applying convolutional neural network (CNN), 39 in total, followed by studies using generative adversarial network (GAN) and artificial neural network (ANN), and some studies exploring the application of recurrent neural network (RNN).

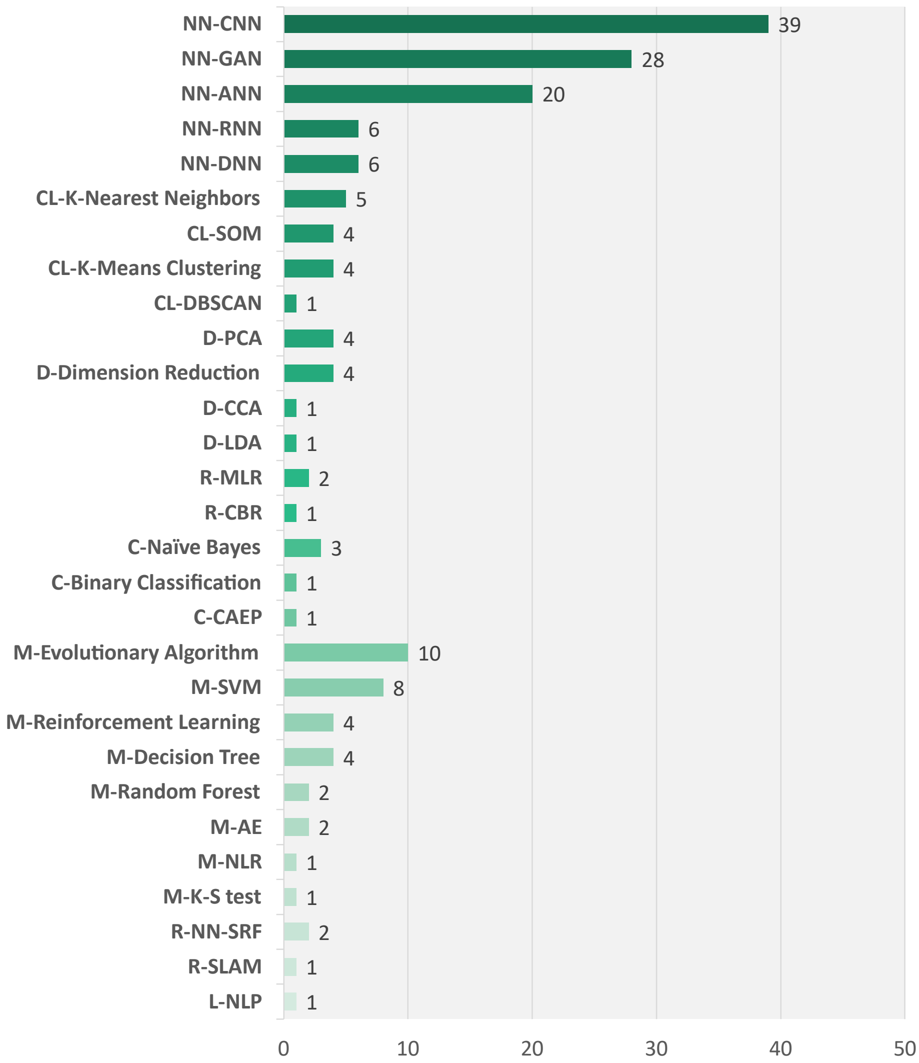


Figure 25. Distribution of Algorithms Related to ML.

* NN - Neural Network, CL - Clustering, D - Dimension Reduction, R - Regression, C - Classification, M - Multipurpose, R - Robotics, L - Language Processing

2.5. Correlation Analysis

2.5.1. Cross-Representation

The research tasks of the 621 literatures selected were classified into 9 categories in section 2.4 above. In order to systematically investigate the application of AI technologies in various aspects of the construction field, the main 5 categories of Generative Design, Digital Fabrication, Deep Image, Recognition and Classification, and Performance and Prediction are further defined. A detailed summary and analysis of the 84 articles involved are also presented.

These summaries and analyses will focus on answering the first 3 questions in section 1.4 above:

- Which AI technologies are employed in which research fields or orientations?
- Within the same field, are there any advantages or disadvantages in the application of the technologies?
- What are the potentials or possibilities of AI technology implementation in terms of sustainable building design?

Generative Design

Research related to generative design includes research on the use of neural networks for style transfer between architectural images and other art images, research on the generation of architectural images including floor plans and façades, exploration of architectural structures and architectural design processes using deep learning, research on the selection and optimization of architectural design solution sets, and research on the generation of architectural plans based on diagram structures.

- Style Transfer

Style transfer is a method for the generation of new images through the intervention of style images. To realize the stylization of the content image, it relies on AI to globally transform the content image and the style image in terms of spatial structure, color change and texture synthesis. In recent years, the rapid development of AI has led to significant progress in style transfer technology. Style transfer plays an important role in art creation and design, image and video editing and processing, information hiding, and so on. Many scholars are also trying to combine style transfer with architectural disciplines.

Campo et al. created databases of Baroque-style architectural images and modern high-rise architectural images and used the pre-trained VGG-16 architecture in convolutional neural networks to achieve 2D-to-3D style transfer(52). Within each layer, there are many convolutional kernels, and the learning process of the convolutional neural network is to define the weight of each kernel, which controls the system's extraction of specific visual features from the input in reverse. In another study by Campo, the PG-GAN architecture proposed by Nvidia was used for 2D-to-2D style transfer of standard plan images, terrain maps, and abstract architectural/artistic images(53). When a generative adversarial network is trained, it learns to connect and define the texture, color, and geometric attributes of the visual space between images in the dataset, so that the trained generative adversarial network can be used to generate new images.

Özel et al. selected five landmark buildings in the center of Los Angeles and used drone-captured building images as target images, while an artist's art image served as the image library for style transfer(54). In order to transfer the style to the selected area and building, rather than the entire image, the study chose semantic image segmentation in computer vision (CV) to recognize and extract building elements using VGG-19. The process of style transfer applied the convolutional neural network architecture proposed by Ruder and linked the programmatic modeling technique and mesh operations such as stretching and rotation to two-dimensional images. he visual content of the style transfer image was extracted through programmatic modeling software, transformed into a three-dimensional model of the building, and thereby completed the style transfer from 2D images to 3D geometric shapes.

- Image Generation

Research on image generation is mainly based on supervised learning, which involves constructing a mapping between image pairs through neural network training.

Zandavali investigated an alternative method for automatic bricklaying using image representation, by training a Pix2Pix architecture with a conditional generative adversarial network on boundary images of walls and their corresponding filled brick patterns as input images(55). The trained model can generate segmented brick wall patterns based on the input boundary pattern. Newton conducted experiments on image generation using a small dataset of 45 plans of Le Corbusier's works and compared the performance of wGAN with three different types of data augmentation, namely noise, rotation, and noise and rotation, against the performance without any data augmentation(56). The results showed that noise augmentation was the most effective method in this study. Mohammad employed a generative adversarial network for generating façades(57), while SILVESTRE et al. explored an algorithm using deep convolutional neural networks for generating two-dimensional architectural perspectives(58).

Hao Zheng developed a floor plan generation model based on manually designed data, which can predict the location of bedroom furniture by inputting boundary data of rooms, doors, and windows. What sets this study apart is that the design data was vectorized to directly represent the design elements in CAD drawings, rather than being represented as pixelated image data, thereby improving the accuracy and precision of learning and prediction(59).

In another study conducted by Zheng Hao et al., Generative Adversarial Networks were used to generate city plan diagrams. By mapping the site information such as roads, rivers, green spaces and the layout of buildings, the model was able to generate urban layouts under specific site conditions. The study collected data from eight different cities and conducted cross-testing to analyze the design strategies of different types of cities(60).

- Generative Design Process Exploration

Miguel employed a deep generative model - the Variational Autoencoder (VAE) - for the generation of three-dimensional geometric shapes. The trained network is capable of recognizing wireframes that represent the core geometry of buildings and extracting new points from the learned continuous latent distribution, outputting their corresponding connection maps to generate new wireframes(61).

Yetkin developed a framework that uses ANNs to optimize the structural design process. The study proposes a correlation between the design space and the target space, allowing designers to explore multiple solutions by controlling the target structural performance(62).

Rodriguez conducted a test on the implementation capability of a multi-agent system based on ANNs in the architectural design process. The study is based on self-organizing map algorithms and uses their behavior in topology to generate geometric bodies of architectural structures(63).

Ardavan and Pedro used point clouds as a representation of geometric data and utilized autoencoders (AE) for generating design solutions(64).

There are also some studies that explore the generation of architectural and urban spatial layouts through reinforcement learning. For example, Koh used reinforcement learning to generate maps in a vectorized map mode similar to the Pokémon game(65). In this mode, the computer determines whether to expand the map and add new elements, thus generating a reasonable urban space. This understanding of the game nature of architectural and urban data greatly expands the possibilities of generative design. Similar studies, such as an experiment by Akizuki et al., modularize design elements and decide on the optimal solution through a reinforcement learning framework(66). Veloso and Krishnamurti used reinforcement learning to generate architectural spatial layouts for different terrains. The reinforcement learning module can comprehensively consider various indicators such as shape, area, and topological relationships to generate reasonable architectural solutions(67).

- Optimization of The Design Solution Space

The widespread application of design generation and optimization systems has brought great potential for solving design problems. However, they lack effective organizational methods to handle the excessive design options they produce, leading to excessive redundancy and dispersion of the designer's overall perception of the design set. As a result, some studies have focused on clustering and evaluating the design solution space to achieve condensed solutions and enhance heterogeneity.

Shermeen conducted a series of studies aimed at condensing the solution space and increasing heterogeneity in generative design systems. He explored the potential of the K-means algorithm to cluster design forms into groups of similar forms, but the results did not yield representative candidates for each cluster(68). In another study, he developed a new method for shape clustering using the KM-SC algorithm based on the Hungarian algorithm and the Euclidean distance metric, which was combined with K-medoids clustering. Finally, he applied clustering as a representation method for the design set in a generative design system, resulting in the generation of a new prototype(69).

Binary classification is a method for generating predictive models, where the model outputs a binary result when given input variables, allowing for classification of items into two groups. Gewirtzman designed a cyclical process consisting of optimization, crowdsourcing, and classification, allowing participants to experience 3D models of apartment units from a first-person perspective and evaluate them. Using the evaluation data, a binary classification algorithm was used to generate a predictive model(70).

In Christan's research, the model was able to learn from the evaluations of solution samples by designers and select solutions that meet their personal aesthetic or abstract design quality standards. Principal component analysis (PCA) was used to reduce dimensionality during the process(71).

Digital Fabrication

The research on the application of AI technology in the field of digital fabrication mainly involves utilizing its algorithms to study the properties of building materials and the preparation of various materials, as well as assisting the fabrication process through the control of robotic arms and other path planning methods. This technology enables human-machine interaction or collaboration between robots and humans in the construction process.

- Material Preparation and Material Properties

Rossi employed convolutional neural networks to learn the relationship between the working path of a robotic arm and the shape of a bent metal plate. Initially, the robotic arm was used to bend the metal plate along different paths, and RGB values were used to represent the coordinates of each control point on the surface of the metal plate. This dataset was then used to train a generative adversarial network, which could generate the working paths of the robotic arm to achieve specific bending effects(72).

Similarly, Thomsen used the Pix2Pix architecture in a generative adversarial network to train a model to generate knitted images from input shadow images of the knitted fabric. The network was trained using samples of knitted images as outputs, and the trained model could generate woven images using texture images as inputs(73).

Dan Luo et al. focused their research on non-uniform materials with different cross-sectional properties, namely rubber sheets. They utilized the Long Short-Term Memory (LSTM) network in Recurrent Neural Networks to determine the relationship between material properties and their formal outcomes. They also used Grasshopper, a plugin for Rhinoceros 3D, to mediate between the neural network model and the design process, allowing the trained network to adapt to the architectural workflow(74).

Koshelyuk utilized AI algorithms to monitor and process the conductive behavior and deformation of graphene in order to optimize the pattern of graphene nanosheets (GNP) to maximize sensitivity of the film to specific types of deformation. Decision trees, random forests, and backpropagation deep neural networks were used to test the accuracy of predictions, with the neural network achieving the highest accuracy(75).

- Machine Control

Rossi and Nicholas utilized the Robots plugin in Grasshopper to create a dataset that takes geometric information as input and outputs the configuration of robot joints to train an ANN. By integrating complex path planning and environmental perception through direct human-machine interaction, they were able to achieve their goal(76).

Brugnaro obtained data from the carving process by human experts, using parameters such as tool/workpiece angle, tool/grain orientation angle, force feedback, feed rate, target cutting depth, and target cutting length as input, and cutting depth, length, and width as material output. They used motion capture cameras or force sensors to obtain data and trained a regression model(77).

Pinochet aims to propose an interactive model that goes beyond the current design-manufacturing dichotomy in CAD-CAM applications. The study uses body posture as real-time input and reads human depth images using motion tracking sensors through machine learning algorithms. The model is trained using an adaptive naive Bayes classifier to extract features, allowing the machine to interpret data and determine further operations based on the designer's gestures(78).

Devadass used machine learning algorithms to analyze production parameters and constraints, and to make real-time predictions of robot manufacturing paths. The study utilized self-organizing maps (SOM) to analyze and map the relationships between input parameters, such as the cutting angle of the workpiece, generated product information, and their constraints, and used K-nearest neighbors (KNN) and backpropagation algorithms(79).

- Guidance Of the Fabrication Process and Inspection of The Quality

Wu, Dimopoulou, and their colleagues have developed an algorithm for automatic identification of bamboo nodes, aimed at improving production efficiency and quality control for bamboo product manufacturers. In their study, they employed a convolutional neural network model to train on labeled images of bamboo, enabling the model to detect and identify bamboo nodes. Additionally, they developed an augmented reality (AR) -based application that overlays virtual bamboo node information onto the actual bamboo, facilitating more accurate and efficient construction processes for bamboo product manufacturers(80).

Deep Image and Mixed Reality

AR is a technology that extends information to real-life scenes, while Diminished Reality (DR) is a technology that visually removes existing objects and overlays background images in the target area. By combining AI technology with AR and DR, they can be applied to urban street scene images to evaluate the living environment.

Cao et al. constructed a U-net deep learning network to automatically identify the sky area from 360-degree camera images by learning from the original images and manually labeled sky image masks. This allowed them to evaluate the sky view factor (SVF) of the living environment(81). Fukuda conducted research on diminished reality and developed the Sky-DetectNet deep neural network based on SegNet to segment building and sky areas. Then, image restoration techniques were used to generate sky images in the building areas(82).

Kinugawa and Takizawa utilized the Pix2Pix architecture to recognize depth maps in Google Street View images and built a convolutional neural network model that showed better predictive performance when trained on RGBD images for street view evaluation models(83). Steinfeld extracted street view images from 9 cities from Google Street View and processed the data into a raster image pair: one processed into an RGB image and the other processed into a grayscale depth map, then trained Pix2Pix and StyleGAN models to generate city street view images(84). Takizawa used a 3D model and selected 50 points to extract omnidirectional RGB and depth images merged into four-channel RGBD images. They trained two deep convolutional networks, GoogLeNet and AlexNet, on the three types of image data and predicted subject preferences in virtual city space. They concluded that the GoogLeNet model trained on RGBD images had the lowest error rate(85).

Kato utilized a CMP database to train a model for identifying building elements in street view images and extracting their colors. The K-means method was then employed to cluster these colors and create a color palette, which serves as a fundamental basis for making decisions in architectural and urban design(86).

Recognition and Classification

- Recognition of Three-Dimensional Space or Form

Yetis et al. selected Rhinoceros 3D as their development environment and generated a dataset of three-dimensional building elements. They attempted to automatically label and classify these elements using logistic regression, KNN, linear support vector machines, kernel support vector machines, naive Bayes, and decision tree algorithms. The results showed that kernel support vector machines achieved the highest accuracy(87,88).

Peng et al. first introduced a sampling method based on 3D contour lines, which could generate a two-dimensional image to represent the three-dimensional space of specific observation points. They trained a convolutional neural network model to extract features from the sampled images and then classified their corresponding spaces(88). Newton used 3D convolutional neural networks for 3D matrix operations to classify buildings based on their shape features(89).

- Recognition of Two-Dimensional Design Elements

Ferrando used AI techniques to study the spatial configuration of multiple instances in an architectural dataset of religious building plans, including mosques and monasteries, in order to classify buildings. Due to the limited size of the dataset, the " Leaving Out One Cross Validation" (LOOCV) method was used, and the results proved to be the most accurate for gradient augmented tree and random forest predictions(90).

Uzun uses a convolutional neural network trained with 200 samples to classify building plans and sections. To solve the problem of insufficient prediction accuracy for small data sets, the study uses a migration learning method to make the training more robust(91). MEI YEE NG also proposes a convolutional neural network model to classify technical drawings such as sections, plans and façades(92).

Kim et al. trained convolutional neural networks to detect and identify features of chairs in images, and trained six models to determine their function, material, seating capacity and style respectively(93). They also tried the application of R-CNN in another study to identify indoor elemental features, and the detection results of R-CNN were more accurate, but slow in training. Therefore, Faster RCNN neural network was used in the study, the accuracy of the detection model was 92.6%, and the average accuracy of the model with 9 judgment features was 83.2%(94).

Xing Shi et al. used semantic segmentation and convolutional neural networks in the U-net framework to train a dataset consisting of more than 150 building façades to identify walls and windows in building façades, so as to automatically complete the calculation of building window-to-wall ratios and assist in the calculation process of building energy consumption (95).

Kvochick implements a technique to circumvent the data starvation of neural networks by employing a network similar to a full convolutional autoencoder to generate data first, which is then resampled to 1024×1024 pixels for training. The validation set is created by manually annotating a completed floor plan of a building(96).

Performance and Prediction

- Performance Mapping Modeling

Most of the research on performance mapping models using AI approaches is based on ANN. Asl introduced the Energy Modeling Machine (EMM), an AI-based tool that uses ANNs and an Boosted Decision Tree (BDT) approach trained on existing simulation results to predict the energy performance of buildings without the need for actual simulations(97). Lorenz et al. trained ANNs to simulate predictions of daily illumination, simplifying the time-consuming process of simulation(98).

Zhang first used global sensitivity analysis to identify the key variables affecting thermal performance in grain silo buildings. Then two ANNs were developed to build simple statistical energy models to predict the thermal performance of various building forms in grain silo buildings(99).

Lin first generates a physical solution by twisting the dynamic model and records the corresponding physical and environmental data through the Arduino platform for sample training. The trained model controls the set of steering parameters of the dynamic model under the target environmental parameters and field conditions, which are then passed to the mechanical model device through the Arduino platform to obtain the final predicted optimized morphological results(100).

Ghandi used occupant's bio-signals (such as heartbeat, sweating and skin conductance, sweat secretion, muscle tone and body temperature) to spatially respond to their senses and needs, including changing the size, location and shape of windows, the overall shape of the space, etc., (101).

In addition, some studies have also trained AI models for simulation prediction of building and urban environment performance based on the powerful image processing capability of conditional generative adversarial networks, which can greatly improve the prediction speed. For example, Mokhtar et al. trained conditional generation adversarial network models based on existing simulation data to predict the wind environment of buildings. The trained models have faster prediction speed compared to conventional simulation software, but the accuracy and precision need to be improved(102).

For the application of neural networks, there are also studies that partially apply reinforcement learning. Jabi used reinforcement learning to evaluate the synergy of fire exits in the early stages of design. In the study, a non-fluid topology was used to represent the building spatial relationships, the location of rooms in the building as intelligences, and the whole building as the environment. An algorithm was designed to simulate the spread of fire in the building. The main driver of the reinforcement learning system was to predict the expected benefits of the model as a whole(103).

Tongda Xu investigated a prototype of environment-electroencephalography (EEG) interaction, selecting EEG alpha power and color (H, S, V) as input and stimulus, and training through color changes to generate a model to keep the subject's alpha waves stable(104). Smith described the development of an intelligent adaptive control (IAC) framework that uses AI to integrate responsive passive envelope control into a building 's integrated conventional environmental control system, which learned its operating strategy from the history of interaction with the environment(105).

In Zhang's research, CityMatrix is an urban decision support system. Users using CityMatrix can examine five urban metrics: population density, diversity of experience, energy efficiency, traffic performance, and solar radiation(99). The first three metrics can be computed in real time, but traffic and solar simulations are time consuming. Therefore, CNN models are trained to predict traffic performance and solar radiation. Later, another study in the MIT-Media Lab City Science lab used SimCity to generate semantic segmentation images of street scenes(106). Then the GAN model trained by cityscapes database is used to generate the streetscape live images. Based on these users can visualize the real-world images of the city in the process of changing the urban design. CHUNG and JENG used web crawling to select social network information and used decision tree algorithm to predict the implicit factors of air pollution(107).

- Design Decision Support

Lin and Huang used the data collected by the Wi-Fi-IPS system as a data source to conduct a comparative study on the environmental behavior differences among different populations. The gradient boosted decision tree (GBDT) algorithm was used for the process of data cleaning, data compression, data analysis and feature prediction(108). Karoji explored the application of recurrent neural networks, using the behavior of pedestrians in shopping malls as data to train a behavior predictor that can infer a pedestrian's direction of travel based on information such as his current location and orientation, and thus guide the design of the mall(109).

Yin et al. used UWB tracking to record the location of each visitor and then fed the data to a K-means clustering algorithm for clustering to find the center of the dwell location. The clustering shows the preferred location of visitors to the exhibit, which helps to change the layout of the exhibition space to improve the user experience(110). Chen has produced a series of interactive maps by collecting call detail record (CDR) data from visitors, inferring visitor behavior patterns, and using AI methods to design simulation prediction tools to support urban design decisions(111).

Rhee extracted data including spatial morphological features of buildings and their surrounding cities. The data were classified to determine the morphological characteristics and types of cities. The buildings were labeled with colors in the process, clustered with KNN algorithm and generated boundaries(112).

Chang uses K-means clustering algorithm to cluster urban spaces with similar characteristics(113). Aschwanden used the KNN algorithm for classification in a similar study conducted(114). Choi proposes a land price prediction system that first constructs a case base based on case-based reasoning (CBR) theory, identifies the features of each data collected as nominal, rank, interval and ratio variables during retrieval, uses Euclidean distance to measure similarity, and performs retrieval based on the KNN algorithm(115). In addition, some scholars represent urban land properties as vector data and train ANN models. By identifying the land use properties of the surrounding parcels, the land use properties of the parcel are predicted(116).

2.5.2. Panel Analysis

Table 6 shows the frequency of the algorithms in the relevant tasks. The data do not correspond to Figure 23 and Figure 24 since some studies used different algorithms at different stages. The results of the correlation analysis show that:

1) Neural Network and Multipurpose algorithms are present in almost all tasks. Algorithms such as clustering, regression, and classification are mostly used for design generation and performance mapping. Dimension Reduction algorithms are more often used in performance analysis and evaluation. Robotics algorithms are mostly used in the field of human-machine interaction (HMI) and machine navigation in the digital fabrication process.

2) GANs and CNNs are most used in image and model generation. Since Huang et al., (117). achieved the recognition and generation of architectural floor plans by Pix2PixHD in 2018, GANs are gradually applied to expand to the fields of style transfer(118), digital fabrication(119) and urban design(120). On the other hand, in the consistent pursuit of accuracy, ANNs have also been gradually explored in the field of design generation(121).

3) Due to the excellent ability of deep mining of image data, CNNs is more often used in the field of semantic segmentation and have become an important tool for image generation (122) and urban, architectural and landscape analysis(123,124).

4) ANNs have unique vector data learning capabilities, and therefore are initially widely applied to performance mapping of physical environments(97,125), and to assist in design decisions. Recently, they can also show powerful capabilities in model generation and optimization.

5) Due to the natural ability of "cyclic" computing, RNNs are extremely sensitive to the sequence of data. Therefore, they are widely used in the process control of robot fabrication (74,126), and design evaluation(127).

Table 6. Correlation Distribution of Algorithms and Tasks.

	I/MG	ST	DO	S-S	DS	HMI	RC	ER	MP	U/BA	PM	PE	BP	SS
NN-CNN	10	4	2	21	1	1	2	1	2	9	2	1		
NN-GAN	20	8	1	2	1	1	3			1	2			1
NN-ANN	5	1	2		6		2			1	8			
NN-RNN			2				3			2		1		
NN-DNN	2	1			1		1	1						
CL-KNN			1		1					4		1		
CL-SOM	1									2				
CL-K-Means Clustering			1		1					1		1		
CL-DBSCAN										1				
D-PCA					1					3				
D-Dimension Reduction				1						3				
D-CCA										1				
D-LDA					1									
R-MLR				1	1								1	
R-CBR										1				
C-Naïve Bayes					1					1		1		
C-Binary Classification					1									
C-CAEP					1									
M-Evolutionary Algorithm	2		3		5	2								
M-SVM	1		1	2	1	1	1	1		3	1	1		1
M-Reinforcement	1				1	1	1			1	1			
M-Decision Tree					1				1		3			
M-Random Forest									1	1				
M-AE	1													
M-NLR	1													
M-K-S test										1				
R-NN-SRF						1	2				1			
R-SLAM						1								
L-NLP				1										

2.6. Research Gap

Researchers in the field of architectural design generally agree that images are the most effective tools for architects to express their design intentions. In terms of image generation techniques, GAN has become the most advanced approach and is widely used in the field of architectural design. In recent years, GAN networks have evolved from CycleGAN(128) to Pix2Pix(129), attracting the attention of architects and proving the learning and generative capabilities of GAN networks in the field of architectural design through the validation of ArchiGAN(130,131) in early 2020. However, although many scholars have built on this foundation and explored it more deeply, there are still some pressing issues that need to be addressed.

Lack of Energy Concern

Most studies have focused on improving the accuracy and creativity of the generated results with the aim of creating more stunning spatial effects. However, this pursuit may sacrifice the active creativity of architects and even raise some ethical controversies, which are not suitable to be discussed here. In addition, the design solutions generated by AI often do not take into account energy conservation, which is unfavorable to the current situation of global energy crisis.

Low Capability Dealing with Complicated Demands

The current commonly used GAN networks still have deficiencies in terms of generative capabilities. When encountering complex requirements, the generated results often fail to achieve the expected results. This indicates that we need to further improve and optimize the algorithms of GAN networks to enhance their performance in dealing with complex design issues.

Do Not Have Comprehensive Implementation in a Complete Project

Many researchers are currently too engrossed in the technology itself and have yet to fully observe the comprehensive effects of AI and human collaboration in implementing architectural design in complete projects. This collaboration is an important and interesting area in the architectural design process. More empirical studies are needed to explore effective human-AI collaboration models for better applications in architectural design.

2.7. Summary

This stage first conducted a 3-level matrix search in the CumInCAD platform to obtain 621 articles and 1236 keywords they contained. By co-occurring the keywords, 27 clusters of AI research in the field of architecture can be obtained. After dividing these articles into regions, this paper makes a cross-sectional comparison in each region and discusses the different development processes and research directions in North America, Europe, and Asia.

By reading and summarizing the articles after 2016, this stage summarized 14 tasks and 29 common algorithms. By constructing the relevance matrix among them, the roles that different types of algorithms can play in different categories of tasks are analyzed, and an attempt is made to answer the question posed at the beginning of this stage: "How AI Can Effectively Help Architects to Solve Which Problems in Reality".

In addition, it is foreseeable that as Neural Network development capabilities improve, architects will no longer be limited to image generation alone. Networks such as ANNs and RNNs will assist in the generation and optimization of vector models. In terms of fabrication, AR and HMI are also gradually forming systematic research and are expected to be applied to more abundant scenarios in the coming years. On the other hand, due to the unique complexity of cities and buildings, the basic AI methods such as Classification, Regression and Clustering will not fade out with the emergence of Neural Networks. On the contrary, they will merge with each other and be used together to improve the overall performance of AI and to play a more powerful role in the field of architecture.

Finally, discussed the research gap for GAN, which is the most widely used in the field of image generation. We need to pay more attention to the active creativity of architects, combine the consideration of energy saving and environmental protection, optimize the generative capacity of GAN networks, and deeply investigate the human-AI collaboration mode to promote further development in the field of architectural design.

Chapter 3. AI Based Methodology

3.1. Introduction

According to the correlation analysis in Section 2.5 above, it can be observed that the GANs have great advantages for applications in image and model generation. The generation of architectural design solutions, on the other hand, is precisely a combination of images and models. Although GAN networks show great potential and application prospects in the field of architectural design, several issues still need to be addressed in this stage. Section 2.6 above presents the current gaps of the current related research.

This chapter will present the strategies of this research for each of the following 3 gaps, and will systematically introduce the relevant methods to be employed in these strategies. These methods will simultaneously address the issues presented in Section 1.4 above.

- Lack of Energy Concern.
- Low Capability Dealing with Complicated Demands
- Do Not Have Comprehensive Implementation in a Complete Project

3.2. Strategy 1 – Empowering Samples

3.2.1. Original Generative Adversarial Network Structure

GAN is a generative model most used for image generation, doing transformation between image forms, image synthesis, and image-based style transfer, etc. In addition, GAN can also be used for classification. Since GAN itself is an algorithmic framework for unsupervised learning, GAN has a wide range of applications in both supervised and unsupervised learning fields.

GAN, proposed by Goodfellow et al. in 2014, is an implicit density generation model that makes the samples generated by the generative network obey the real data distribution by means of adversarial training(132).

GAN consists of a generator and a discriminator. The generator receives the input of random variable z and generates the dummy sample $G(x)$ by the generator. The goal of the generator is to generate as many samples as possible so that the discriminator cannot distinguish between the sources. The discriminator's input consists of two parts, the real data x and the data $G(x)$ generated by the generator, and the goal of it is to identify whether the input samples are real samples or generated by the generator as much as possible, and then provide feedback to guide the generator training (Figure 26).

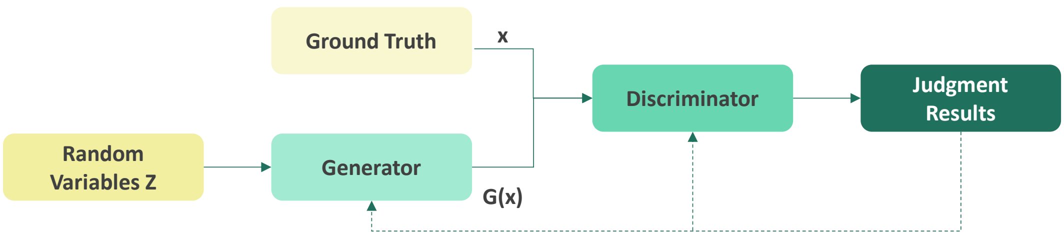


Figure 26. GAN Training Process.

3.2.2. Improved Generative Adversarial Networks

The original GAN is imperfect and has many problems, and the generated results are limited. Many scholars have proposed the following derivative models of GAN for the problems of the original GAN, and each model has its own characteristics (Table 7).

Table 7. Improved Models of GAN and Features.

Model	Features
Conditional Generative Adversarial Network (cGAN) (133)	The constraint term y is added to the input of the generator and discriminator, which can make the model generate samples in a given direction and solve the problem that the original GAN generation results overly arbitrary. However, it needs labeled training data, which has higher requirements on the dataset and does not solve the problem of unstable training.
Laplacian Generative Adversarial Network (LAPGAN) (134)	The concepts of Gaussian pyramid and Laplace pyramid in the field of image processing are introduced, thus solving the quality problem of the generated images, which can generate high pixel high quality images, as long as there is supervised learning.
Deep Convolutional Generative Adversarial Network (DCGAN) (135)	Combining CNN and GAN, using convolution and deconvolution instead of pooling layers, ensures the diversity of results, with insufficient model stability.
Cycle Generative Adversarial Network (CycleGAN) (128)	Having two converters makes the network form a loop structure that does not require pairs of data for training. The process of looping can cause partial loss of information, making the generated images of low quality.
Stacked Generative Adversarial Networks (StackGAN) (136)	The first network model capable of generating real images with a resolution of 256×256 based on text descriptions, which superimposes two GANs, trained in two stages.
Wasserstein GAN (WGAN) (137)	The Wasserstein distance is used instead of the JS scatter in the traditional GAN, thus solving the problems of gradient disappearance and pattern collapse that occur during the training of the original GAN and making the training more stable.
Big Generative Adversarial Network (BigGAN) (138)	The best GAN model for generating image quality so far, the performance has been improved by expanding the model, and the training is more stable. However, it has too many parameters and high training cost.

3.2.3. Improving Sample Quality

In this study, ArchiGAN is used as the basic structure to construct a generative model of low-rise residential building design solutions. It is modeled after Pix2Pix by feeding a large number of residential floor plan samples, enabling it to generate a functional distribution of the building based on the input building exterior profile. However, as discussed earlier, the consideration of "energy consumption", which is embedded in the building design solutions, has not been given sufficient attention during network training. This issue is also relevant to the 4th question would to be addressed in this study:

- What kind of samples should be employed for training?

To address them, the Solar Decathlon (SD) competition entry was selected as a sample in this phase of research to test whether it can make this GAN obtain the corresponding capability. Based on this, the GAN trained in this study is named SD-GAN, and the training sample of SD-GAN will not be limited to building plan generation but will be extended to façade generation.

SD Competition is a global university-based solar building technology competition initiated and hosted by the U.S. Department of Energy in 2002 and has been successfully held in various countries in Asia, America, Europe and Africa. The competition aims to explore innovative models for the integration of solar technology, energy efficiency technology and architectural design. Entries are required to use solar energy as the single source of energy to complete the various inspections and tests required during the competition. The competition is divided into ten categories, which comprehensively examine the realistic feasibility and technical rationality of zero-energy solar homes, and promote zero-energy solar homes from theory to practice in terms of design, construction, operation, and monitoring, etc. After more than two decades of development, the SD competition has become a world-renowned event for the renewable energy and building industry. The entries not only provide many ideas and solutions for the design of low-rise residential buildings, but also contain a large number of innovative and practical advanced technologies that are valuable reference examples for the energy-saving design of contemporary residential buildings.

Building plans and façades are rich in performance-based design factors. The architectural design of the SD competition supports the implementation of various active and passive energy saving strategies. The design of the building's volume influences the proportion of the building's exterior profile, the design of the building's spatial organization and thermal buffer space influences the layout of the building's functions, the design of natural ventilation and lighting determines whether the building has a sunroom and atrium, and the location and angle of active solar equipment plays a decisive role in the form and performance of the building. Therefore, the energy-saving properties of the SD competition entries themselves make it possible to use the SD competition entries as data samples for residential building design solution generation training to achieve energy-saving goals for residential buildings.

Therefore, all of the data for this study came from previous entries of the SD competition. The project manuals and technical atlases of all prior competition entries were collected, from 2007 to 2018. The rich passive energy-saving strategies embedded in the floor plans of the entries may make them valuable as data samples for design solutions generation to achieve passive energy saving in residential buildings.

3.3. Strategy 2 – Improving Generating Capability

3.3.1. Model Construction Objectives and Training Steps

The goal of SD-GAN is to be able to generate a valid and complete building plan or façades based on the input building boundaries. In order to explore the building plan generation process in a more refined way, this study divides the low-rise residential building floor plan (RBFP) generation process into two steps for separate model construction: Model 1 outputs the functional segmentation layout (FSL) based on the input building exterior profile (BEP); Model 2 outputs the building floor plan (BFP) based on the input FSL (Figure 27).

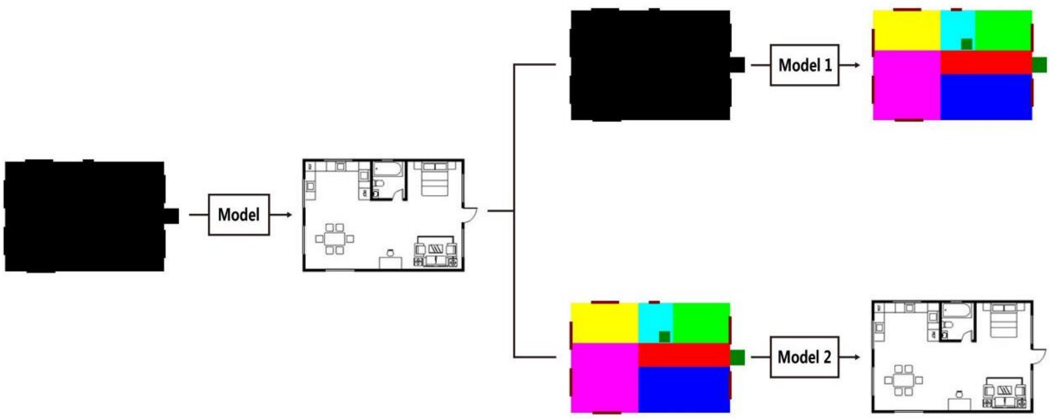


Figure 27. Model Construction and Training Steps.

3.3.2. Model Structure

The base of Pix2Pix, cGAN is a derivative structure formed to solve the problem that the original GAN generation process is too arbitrary and uncontrollable. cGAN controls the direction of generation by introducing additional conditions y and noise z into the generative and discriminative models, and the additional information introduced can be classified labels, text, bounding boxes, key points, etc. The model architecture of cGAN is shown in Figure 28.

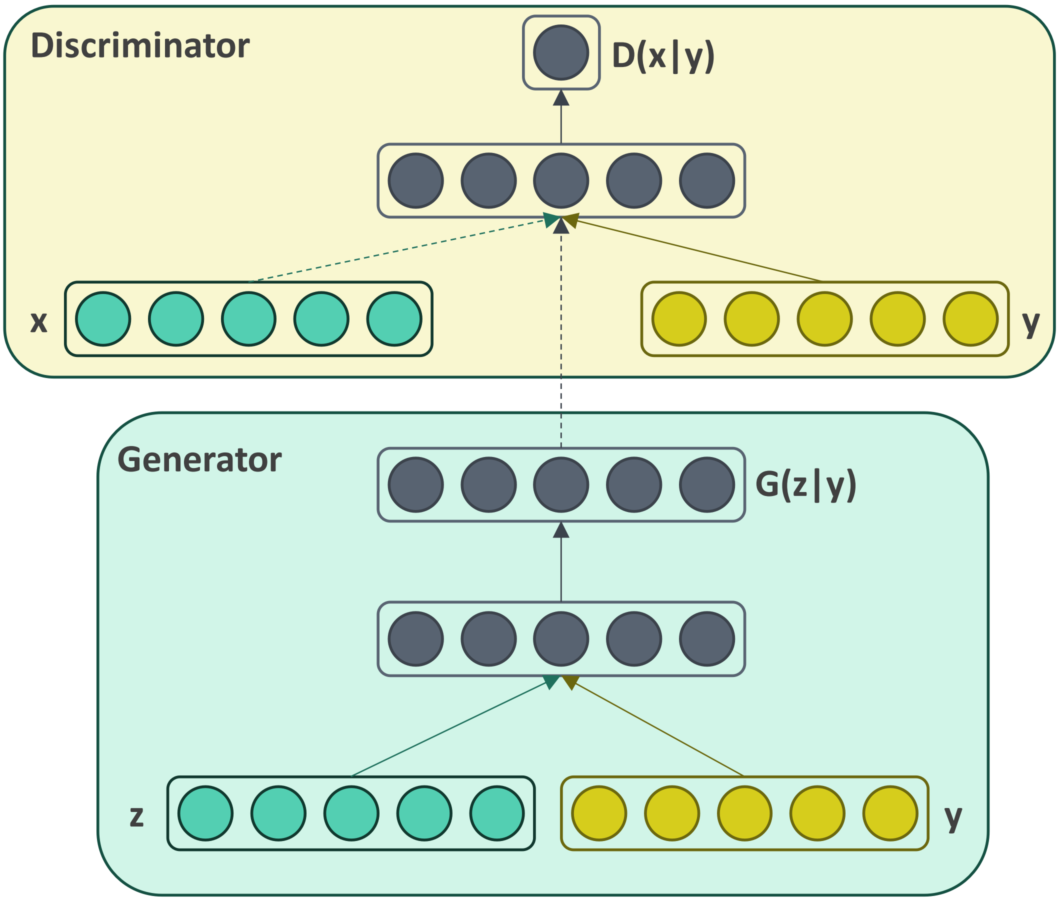


Figure 28. cGAN Structure Diagram.

The model structure of SD-GAN is based on the principle of cGAN, in which the image is used as an additional condition y to generate "fake images" related to this image, thus completing the process of image generation. The two sub-models of SD-GAN have the same structure, and both consist of a generative network and a discriminative network. After iterative training, the generative and discriminative networks can reach an equilibrium state, so that the generated data is very close to the real data.

The objective of Model 1 is to learn the mapping relationship between BEP and FEL (as shown in Figure 29), and the specific process is as follows: (1) The generating network takes the BEP as input x, generates the FSL $G(x)$, then merges $G(x)$ with x based on the channel dimension and inputs it to the discriminating network. (2) The discriminator network receives the input BEP and the FSL generated by the generator network, makes a judgment on whether it is a pair of real images, and makes a prediction of probability value in the range of 0 to 1. The closer the value is to 1 means that the discriminator network thinks the input image pair is closer to the real image.

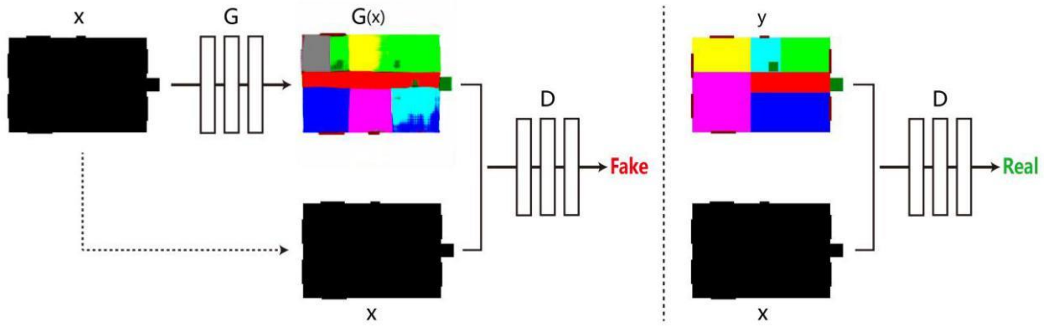


Figure 29. SD-GAN Model 1 Structure.

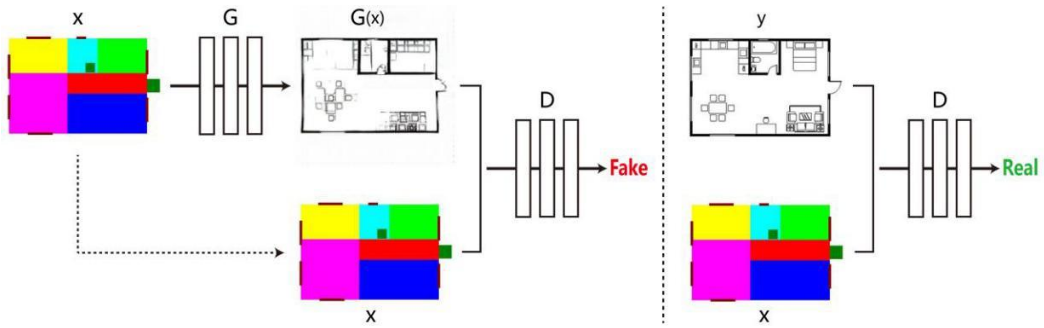


Figure 30. SD-GAN Model 2 Structure.

The objective of Model 2 is to learn the mapping relationship between FSL and BFP (as shown in Figure 30), and the specific process is: (1) The generating network takes the building FSL as input x, generates the BFP with furniture arrangement $G(x)$, and merges $G(x)$ with x based on the channel dimension and inputs it to the discriminating network. (2) The discriminative network receives the input building FSL and the BFP generated by the generative network, and judges whether they are a pair of real images.

Generator Structure

The goal of generator is to generate images that are not recognized as false by the discriminator. The structure of the generative network in the SD-GAN is based on the convolution and deconvolution operations of the Encoder-Decoder. The convolution process is able to extract the features of the image and compress the image, and the deconvolution process is to expand the image size by upsampling to achieve the original resolution. The convolution and deconvolution processes are shown in Figure 31.

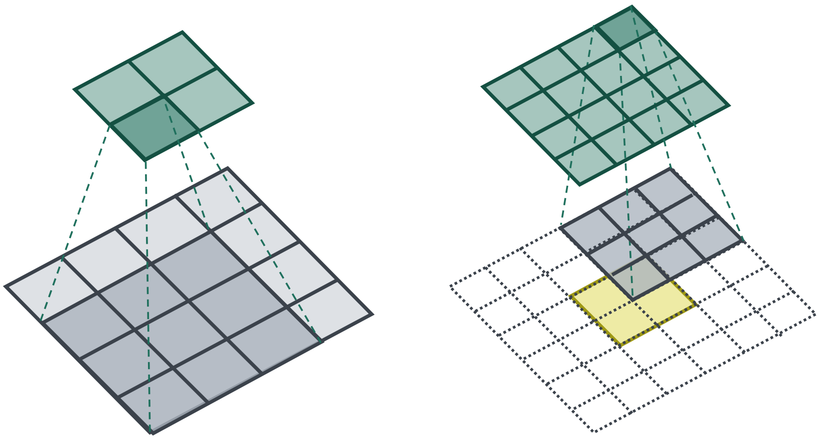


Figure 31. Convolution and Deconvolution Process.

In order to improve the performance of the image-to-image conversion of this model by sharing information between the input and output of the generative network, the generative network structure draws on a fully convolutional structure, the U-net structure(140). This structure is based on the Encoder-Decoder model with the addition of a skip-connection. The left side of the structure is directly connected to the right side, i.e., layer i is directly connected to layer $n-i$, so that the feature information output from the encoder can be directly mapped to the corresponding decoder.

The SD-GAN generative network is symmetrically set up with 8 convolutional layers and 8 deconvolutional layers, and the structure of the generative network is shown in Figure 32. The SD-GAN generator is symmetrically set with 8 convolutional layers and 8 deconvolutional layers. Two 4 × 4 convolution kernels with a step size of 2 and a padding of 1 are used to repeat the convolving of the convolution layers. All layers use BatchNorm and Leaky ReLU (LReLU) as activation functions except for layers 1 and 8, which use only LReLU and start the inversion after reaching the bottleneck layer (Figure 32, red box). For upsampling, the deconvolution process employs a 4 × 4 convolution kernel and a 2 × 2 deconvolution, with a padding of 1. All layers use BatchNorm and Rectified Linear Unit (ReLU) as activation functions except for the first deconvolution layer, which uses TanH (Figure 32, blue box). The unique Skip-Connection of U-net allows each deconvolution layer in the generator's input to include both the previous layer's output and the output of the corresponding convolution layer. This allows the generated image to retain as much of the original image information as possible (Figure 32, green box).

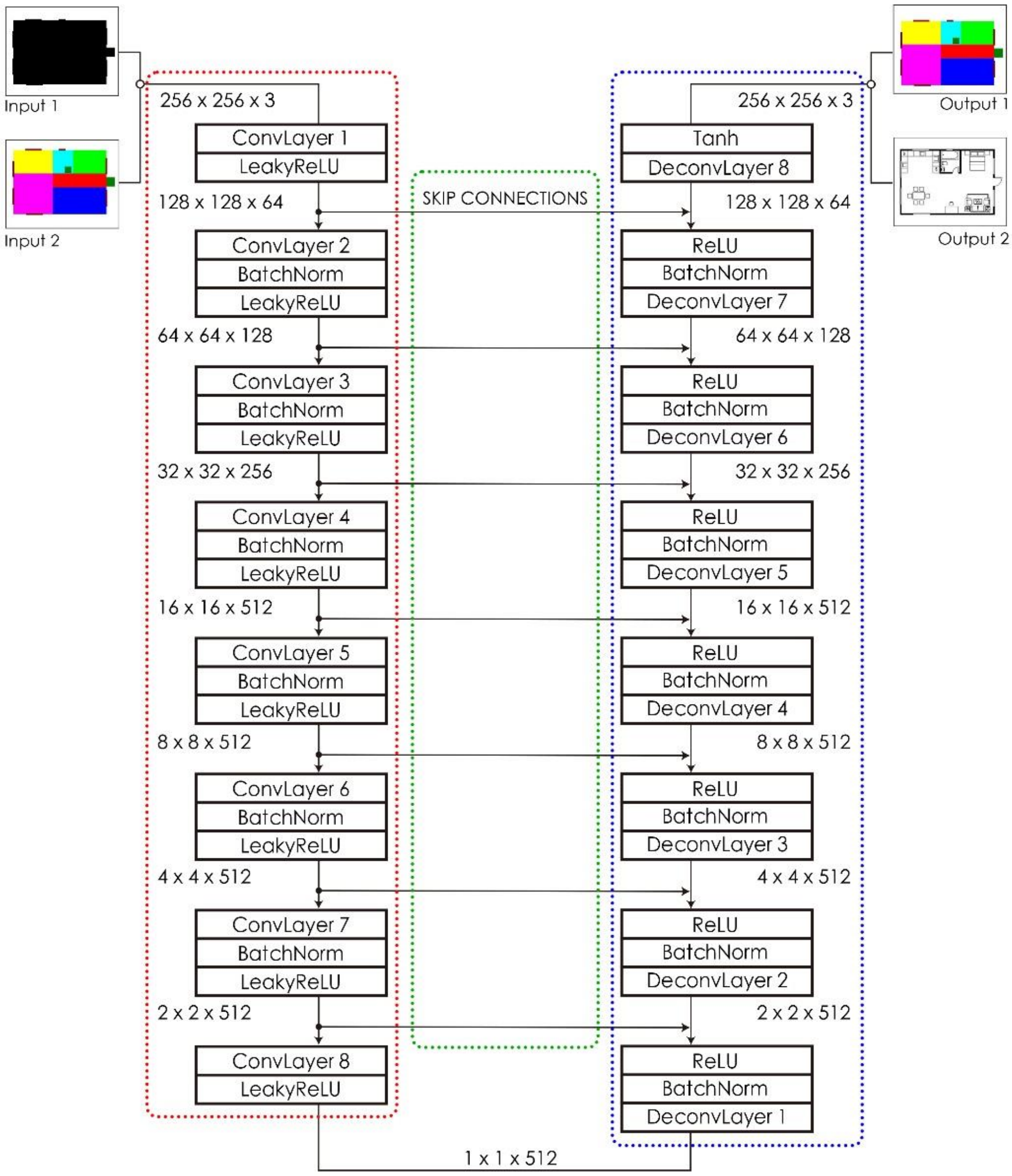


Figure 32. Generator Structure.

The ReLU function is often used as an activation function in neural networks to alleviate the occurrence of overfitting problems, to perform more efficient gradient descent and back propagation, and to speed up convergence. The gradient of the ReLU function can only be 0 or 1, when x is negative, the gradient is 0, and when x is greater than 0, the gradient is 1, as followed Equation (3-1:

$$f(x) = (0, x) \tag{3-1}$$

Compared to the ReLU function, the LRelu activation function (Equation(3-2) solves the problem of vanishing gradients in positive intervals, making it easy to compute and allowing for faster convergence. the LRelu function equation is:

$$y_i = \begin{cases} x_i & f(x_{i)} \geq 0 \\ \dfrac{x_i}{a_i} & f(x_{i)} \leq 0 \end{cases} \tag{3-2}$$

Tanh (Equation (3-3) is a hyperbolic tangent function whose derivative takes values between 0 and 1, while the sigmoid function is between 0 and 0.25. The Tanh function delays the duration of saturation and therefore mitigates the problem of gradient disappearance. the Tanh function equation is:

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{3-3}$$

Discriminator Structure

The goal of discriminator is to discriminate whether the input image is the original image, or a fake image generated by the generator. The discriminator network of the generated model borrows the structure of the Pix2Pix discriminator network and uses the patchGAN structure (also known as Markov discriminator). The discriminative network of ordinary GAN evaluates the truthfulness of the whole image directly, while the principle of patchGAN is to divide the image generated by the generator into multiple patches, i.e., blocks, and the discriminative network classifies each block by truthfulness and falseness, and then takes the average value as the final output of the discriminative model. This reduces the computational effort of the discriminative network and makes the operation faster.

The discriminative network of the generated model consists of a 5-layer convolutional network, and the structure of the discriminative network is shown in Figure 33. The size of the convolutional kernel is set to 4×4, and the first convolutional layer of the discriminative network uses the LRelu activation function, the second, third, and fourth layers use the BatchNorm function and the LRelu function, and the last layer uses the Sigmoid activation function (Equation (3-4). The Sigmoid function is commonly used in the last layer of the neural network and has the advantage of being smooth and easy to derive.

$$f(x) = \frac{1}{1 + e^{-x}} \tag{3-4}$$

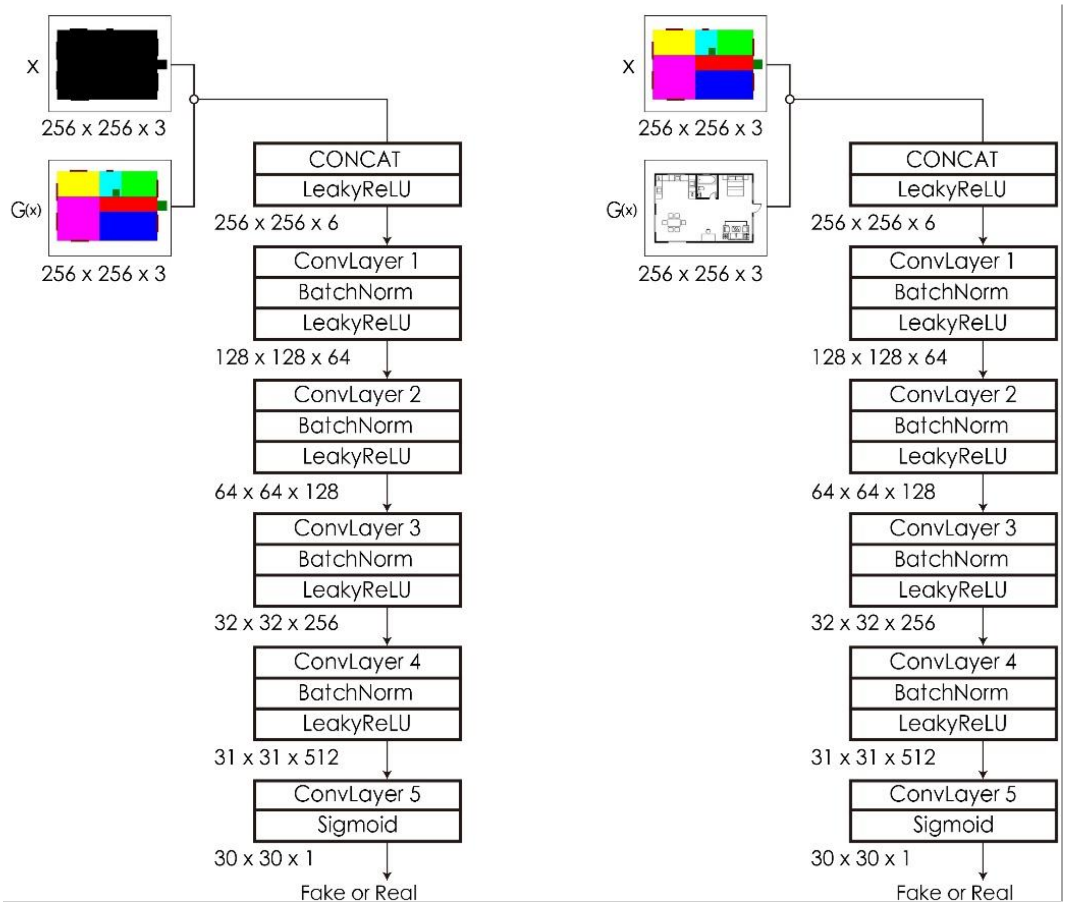


Figure 33. Discriminator Structure.

3.3.3. Training Environment

Loss Function

The loss function refers to the difference between the generated value and the true value. The smaller the difference, the smaller the loss value, the more realistic the generated image is, and conversely, the larger the loss value, the less realistic the generated image is. Therefore, the process of training models is also the process of optimizing the loss value(139).

The loss function of SD-GAN is adapted from the loss function of cGAN, and an additional $L1$ loss function is added beyond the cGAN loss function to make the generated images closer to the real images.

The loss function of cGAN is shown in Equation (3-5 :

$$\mathcal{L}_{cGAN}(G, D) = \mathbb{E}_{x,y}[logD(x, y)] + \mathbb{E}_{x,z}[\log\left(1 - D\big(x, G(x, z)\big)\right)] \quad (3\text{-}5)$$

Since this generative model is mainly for the task of generating building plan or façade images, a lot of information is shared between the input and output of the generative network. In order to ensure the similarity between the input and output, the model additionally introduces the $L1$ loss function, which is the $L1$ distance between the generated image and the input image, to improve the realism of the generated image. the $L1$ loss function is shown in Equation (3-6:

$$\mathcal{L}_{L1}(G) = \mathbb{E}_{x,y,z}[\|y - G(x, z)\|_1] \quad (3\text{-}6)$$

The loss function of the SD-GAN generative network is shown as in Equation (3-7:

$$\mathcal{L}G = \mathbb{E}_{x,z}\left[\log\left(1 - D\big(x, G(x, z)\big)\right)\right] + \lambda\mathcal{L}_{L1}(G) \quad (3\text{-}7)$$

The loss function of SD-GAN discriminative network is the same as Equation (3-5. The generative network attempts to minimize the gap between the true and false images while the discriminative network attempts to maximize this value. Thus, the SD-GAN network ends up with a total loss function as shown in Equation (3-8:

$$G^* = arg \begin{matrix} min \\ G \end{matrix} \begin{matrix} max \\ D \end{matrix} \mathcal{L}_{cGAN}(G, D) + \lambda\mathcal{L}_{L1}(G) \quad (3\text{-}8)$$

Hardware and Software Environment

Usually, AI training needs to be provided with enough computational resources and storage space to be able to handle large amounts of data and perform complex computational tasks. Also, the AI training environment needs to provide some development tools and frameworks, such as TensorFlow, PyTorch, etc., to facilitate the implementation and debugging of algorithms by users. The environment configuration settings for this model training experiments are shown in Table 8.

Table 8. Experimental Environment Configuration Parameters.

Item	*Configuration*	*Item*	*Configuration*
Operating systems	Windows10	Compilers	PyCharm
CPU	AMD2600X	CUDA	CUDA10.1

Item	*Configuration*	*Item*	*Configuration*
GPU	RTX2080Ti	CuDNN	CuDNN7.6.5
Development Languages	Python3.7	Deep Learning Framework	Pytorch1.7.1

Basic Training Parameter

Epochs: An epoch is when all the data is put into the network for a single forward calculation and backpropagation. However, the training of a model often requires many iterations to reach a state of convergence. In this study, the model was under-fitted when the number of iterations was 300, moderately fit when the number of iterations was 400, and over-fitted when the number of iterations was 500. Therefore, the number of iterations for all experiments in this study was set to 400.

Learning Rate: Since the mechanism of neural network parameter update is based on gradient descent and back propagation, the adjustment process is to back propagate the error to the network parameters and thus fit the sample output, which converges to the lowest value of the loss through multiple fits, i.e., the global optimal solution. The learning rate represents the distance of each step, so it determines whether the model can converge to the minimum and how long it takes to converge to the minimum.

When the learning rate is set small, the learning speed is slow, with long convergence time and overfitting problem. When the learning rate is set large, the network learns faster, but it tends to oscillate, and the model does not converge to the minimum. Only a suitable learning rate can make the objective function converge to the global minimum in a suitable time, as shown in Figure 34.

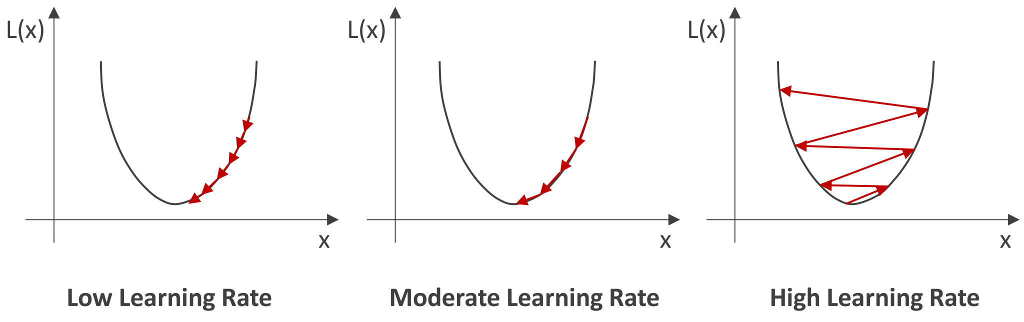


Figure 34. The Effect of Learning Rate Takes on Model Training.

The empirical value of 0.0002 is often used for the learning rate, and the learning rate was set to 0.00002, 0.0002, and 0.002 for the experiments. It was found that when the learning rate was 0.00002, the gradient decreased slowly. When the learning rate was 0.002, it converged too fast but crossed the optimal value. When the learning rate was 0.0002, it could converge to the lowest value in a suitable time (Figure 35).

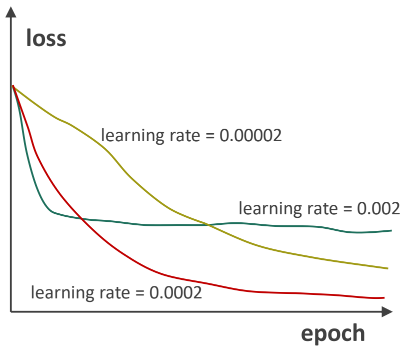


Figure 35. Model Convergence with Different Learning Rates.

Based on the above elaboration, the experimental learning rate settings for this study were all 0.0002 initially. The optimization method is chosen as Adam with momentum parameters β_1= 0.5, β_2 = 0.999.

3.3.4. Evaluating Training Results

In order to identify the generation effect of SD-GAN more comprehensively, the generation results need to be evaluated from both subjective and objective aspects. And to fully answer the 5^{th} question posed in this study:

- How will the training results be verified or evaluated?

For the subjective evaluation, this study plans to distribute the scores in the form of a questionnaire directed to architects and graduate students with architectural education backgrounds. The questionnaire needs to be considered differently according to different training stages and generation contents. Both the clarity and accuracy of the generated images will be compared, and the aesthetic and energy efficiency performance of the generated solutions will be subjectively judged.

For the objective evaluation, firstly, the image similarity between the generated results and the ground truth should be examined. Secondly, it is also necessary to test whether the generated results comply with the local codes related to architectural design. Finally, the necessary energy consumption simulation comparison between the original and generated solutions is also required to quantify the energy efficiency performance of SD-GAN.

Not to be neglected is the 6th question facing this study:

- If the training results do not meet the requirements of the study, how can they be improved or modified?

When the evaluation results are unsatisfactory, this study will take more complex operations, including data augmentation, generator replacement, and human correction. In order to avoid the impact on the simulation results in the empirical study as much as possible, the human correction in this study is based on the principle of minimum correction. i.e., only the generated results that do not comply with the architectural design codes and extremely out of the traditional design perception scope will be corrected.

3.3.5. Data Augmentation

Deep learning network training frequently requires a substantial amount of training data. Insufficient data samples often lead to overfitting problems. However, in practical research, the amount of data that can be directly collected is often limited. Meanwhile, manually collecting and labeling data is time-consuming and arduous. Therefore, data augmentation methods have emerged. These methods can expand the data set similar to the real data based on the original data to improve the generalization ability of the model and thus the accuracy of the prediction. The existing data augmentation methods are classified into two categories: supervised data augmentation and unsupervised data augmentation(141–143).

Supervised Data Augmentation

Supervised data augmentation methods are divided into single-sample data augmentation and multi-sample fusion data augmentation.

- Single-Sample Data Augmentation

The single-sample data augmentation method is a transformation operation around a single sample itself, which is divided into two categories: geometric transformation and color transformation.

Geometric transformation operations include horizontal or vertical flip, random rotation, translation, crop, deformation scaling, affine transformation, etc. on data images. Among them, flipping, rotating, and panning would not change the size and content of the image. Affine transformation refers to multiple operations such as cropping, rotating, converting, and mode adjustment on the image at the same time.

Color transformation includes adjusting the brightness, contrast, saturation of an image, or adjusting the parameters of certain colors, changing their color channel space, etc. Common color transformation operations include adding noise, blurring, and sharpening, color transformation, erasing fill, etc. The noise-based data augmentation is to superimpose a certain amount of noise randomly on top of the original image by certain methods, and the commonly used noises are salt and pepper noise and Gaussian noise(143). The salt and pepper noise is controlled by algorithms to control the amount of noise and randomly generate some black and white stray dots to form light and dark dot noise(143). The Gaussian noise is a sort of noise in which the probability density function obeys the Gaussian distribution (i.e., normal distribution).

- Multi-Sample Fusion Data Augmentation

A representative algorithm of multi-sample fusion data augmentation is Mixup. The core idea of Mixup algorithm is to randomly mix two training samples and their labels in a certain ratio(142). This mixture can not only increase the diversity of samples, but also make the decision boundary transition of different categories smoother, reduce the misidentification of difficult samples, improve the robustness of the model, and be more stable during training.

Unsupervised Data Augmentation

Unsupervised data augmentation includes two types, one is based on deep learning models to learn the distribution of data and randomly generate data sets similar to the sample data, which is commonly used for sample generation using generative adversarial networks. The other category is to learn the data augmentation method that is suitable for the task at hand through a model. The most representative one is AutoAugment proposed by Google, which is based on the basic idea of using augmentation learning to find the best image transformation strategy from the data itself and learning different augmentation methods for different tasks(141).

Compared with ArchiGAN, SD-GAN will have more diverse types of functions for building plan samples. The functions to be generated will be raised from 6 to 10 categories. When the input has only simple information of BEP, it may cause the network to be indecisive. If such a situation occurs, data augmentation will be used first to enhance the building plan generation capability of SD-GAN.

3.3.6. Generator Replacement

In general, replacement generators can cope with the following scenarios:

Improving performance

Replacement generators can try new architectures, algorithms, or parameter settings to improve the performance of the generator. This may include deeper network structures, more complex loss functions, or more advanced generative models. By replacing generators, researchers and developers can explore different design options to obtain better generative results.

Increasing Diversity

Generator replacement can be used to increase the diversity of model generation samples. Sometimes, the original generators may produce similar outputs or have pattern bias. By replacing generators with different architectures or training strategies, the diversity of the generated samples can be promoted, making the generated results richer and more diverse.

Adapting to New Tasks or Data

Replacement generators can provide better adaptability when facing new tasks or data. Different tasks may have different requirements on the input and output size of the generator, feature representation, or the type of samples generated. By replacing the generator and retraining it for the new task or data, the generator can be better adapted to the new context and requirements.

Technology Advances

The field of deep learning is constantly evolving, and new techniques and algorithms are proposed. By replacing the generator, the latest techniques can be applied to the generative model, thus driving the development and improvement of the model. For example, when new generative model architectures (e.g., variants of GAN), regularization methods, or optimization algorithms emerge, the replacement generator allows the model to benefit from these latest technological advances.

Similarly, compared to ArchiGAN, the SD-GAN façade sample flattens the façade of the building. At the same time, the number of components of the building façade has also increased. These changes in learning and generation tasks pose a great challenge to the learning-awareness capability of the SD-GAN generator. Therefore, the original generator U-net is replaced with the updated U-net++, HRNet, and AttU-net, respectively, for the training of building façade generation in this study. After that, their generation results will be evaluated in a cross-sectional comparison. While determining which generator is more suitable for building façade generation, the generative capability of SD-GAN could be further improved.

3.4. Strategy 3 – Empirical Study

3.4.1. Case Background

To validate the feasibility and effectiveness of the SD-GAN proposed in this study, 3 actual residences in Jianchang Village, Beijing, were selected as the cases for the empirical study (Figure 36). The relevant information was fed into SD-GAN and the corresponding residential building plans and façades will be generated. Subsequently, the existing and generated solutions will be simulated for energy consumption, and the result will be analyzed and discussed.

Figure 36. Site of the Cases.

The site is the most remote township in the west of Beijing, located at about 39.5-degree north latitude and 115.5-degree east longitude, with an altitude of 500 m, an average annual temperature of 9 °C, average annual precipitation of 400–600 mm, and a cumulative temperature of 2300–2800 °C.

These 3 cases as the reference group have the advantages of representativeness, controllability, and simplification of energy efficiency assessment in the empirical study. Such a choice makes it more practical to compare and evaluate SD-GAN generated building designs and easier to observe improvements in energy efficiency.

3.4.2. Building Energy Consumption Simulation

This section will provide responses to the last 3 questions posed in section 1.4 above:

- What kind of simulation tools are used for validation?
- Which simulation indicators can be assigned to verify the validity of the approach?

As the research on building energy efficiency has intensified, the application of building energy simulation software in the field of building energy efficiency has received increasing attention in order to simulate the energy consumption of buildings under different working conditions. Since different simulation software has different research focus and relevance, choosing the appropriate simulation software can not only simplify the research, but also get more accurate results.

In order to screen the energy consumption simulation software applicable to this study, a comparative analysis of the widely used software in the market nowadays was first conducted, and the results are shown in Table 9. Through the comparative analysis, it was found that DesignBuilder is simple to operate, strong in visualization, fast in modeling, and intuitive and accurate in simulation results. The model involved in this study is a low-rise residential building, which does not require a complex air conditioning system. Therefore, DesignBuilder energy consumption simulation software was selected for this study to simulate energy consumption for the current situation of the project and the solutions generated by SD-GAN in order to simulate and analyze the full energy performance and economic performance of the building heating and cooling.

Table 9. Comparative Analysis of Energy Consumption Simulation Software.

Name	Simulation Object	Advantages	Disadvantages
Ecotect	performance analysis at the early design stage	Easy modeling, fast calculation, and intuitive output results.	Calculation accuracy is not high and only applicable to initial design.
EnergyPlus	simulation of building units, surroundings, and HVAC systems	Detailed energy consumption solution, advanced algorithm, can be effectively combined with other software.	Complex operation and high requirements for operators.

Name	Simulation Object	Advantages	Disadvantages
DesignBuilder	simulation of building units, surroundings, and HVAC systems	Simple operation, detailed output, intuitive and accurate, high visualization.	Poor ability to simulate complex air conditioning systems.
PKPM	energy-saving design for new construction, renovation and expansion	Developed based on AutoCAD, accurate thermal performance calculation.	Limited parameter settings and difficult to confirm the accuracy of the integrated results.
DOE-2	simulation of building units, surroundings, and HVAC systems	Strong professionalism, wide range of modules, detailed report output.	Complex operation, slow operation, and error-prone equipment energy simulation.
DEST	simulation of building units, surroundings, and HVAC systems	Easy modeling, openness and expandability.	Cumbersome parameter setting and low reliability of simulation results.

In order to facilitate cross-sectional comparisons between the original and generated solutions, the following simulation parameters need to be set uniformly:

Occupant Settings

In energy efficiency simulations, the behavior and habits of occupants have an important impact on building energy consumption and comfort. In order to maintain consistency in comparison, parameters such as the number of occupants, work and rest time, and temperature preference need to be set uniformly. This ensures that occupant behavior patterns have the same impact on the results when comparing different scenarios.

Indoor Thermal Perturbation Setting

Indoor thermal disturbance refers to indoor heat sources due to human activities, lighting, equipment, etc. To ensure the accuracy of the comparison, the parameters of indoor thermal disturbance, such as intensity of human activity, lighting thermal power, and equipment thermal power, need to be set uniformly. This can make the results of comparison more reliable and exclude the variability of indoor thermal disturbance in different schemes.

External Envelope Settings

The exterior envelope is the external enclosure wall, roof, windows and doors of the building and other parts, which has an important influence on the thermal resistance and heat capacity performance of the building. In order to ensure the equality of comparison, the parameters of the external envelope need to be set uniformly, such as the thickness of the wall and the heat transfer coefficient. This can make the comparison results more comparable and exclude the influence of the variability of the external envelope on the results.

Basis of Simulation Calculation

In the energy efficiency simulation, calculations need to be based on relevant design codes and standards. These codes include building energy efficiency design standards, thermal performance calculation methods, etc. In order to ensure the accuracy and integrity of the comparison, the same codes and calculation methods need to be uniformly used for the simulation calculation. This ensures that the results of the comparison are based on the same benchmarks and calculation basis, thus making the comparison more reliable and comparable.

Uniform settings of the above simulation parameters can eliminate the variability between different solutions and ensure the accuracy and reliability of the comparison. This allows for better cross-sectional comparisons between the original and generated solutions and yields a comprehensive assessment and comparison of energy efficiency and design performance.

3.5. Summary

Based on the research gaps presented in Section 2.6, this chapter proposes corresponding strategies to address them, briefly:

- Lack of Energy Concern.

Introducing SD competition entries that emphasize energy efficiency and sustainability to empower the samples.

- Low Capability Dealing with Complicated Demands

Applying data augmentation and generator replacement in different scenarios to purposefully enhance the generative power of SD-GAN to cope with more complex task requirements.

- Do Not Have Comprehensive Implementation in a Complete Project

Conducting an empirical study on 3 different shape cases of Jianchang Village in Beijing, including: building plan generation, façade generation, and the corresponding energy consumption simulation and comparative analysis. The empirical study will be implemented to validate the potential of collaborative human-AI architectural design and to further discuss the numerous changes brought about by this design paradigm shift.

Chapter 4. Empowering Samples

4.1. Introduction

Data labels are critical to the results generated by AI. In machine learning, data labels refer to the correct answer or label for each sample in the training data, and these labels are used to train the model to learn how to perform classification, prediction, or recognition. If the training data is labeled inaccurately or lacks representation, then the trained model will also show biased or inaccurate prediction results. For example, if an image classifier is trained with the wrong labels, the classifier may not be able to correctly classify images. Therefore, it is crucial to ensure that the training data has accurate, complete, and representative labels.

In previous studies, there is a lack of generation of architectural design solutions addressing energy efficiency. This chapter will explain the method of introducing SD competition entries to empower the training sample.

The SD competition is a very meaningful competition that aims to promote sustainable development and environmental protection. Selecting the entries of this competition as the training data for SD-GAN will potentially enable it to learn energy-efficient housing generation patterns that are more in line with the requirements of sustainable development and environmental protection, and thus better achieve the goal of energy-efficient housing generation.

For the entries of SD competition, different data may have different value ranges and data distributions due to the diverse form types and technical features, which may affect the training and prediction effects of the model. Therefore, normalization of the data is an important step, which can help us map the data to a uniform range and eliminate the quantitative differences between different features, making the model more stable and accurate. This chapter will discuss how to normalize these data for building plan and façade generation.

4.2. SD Competition

The SD Competition is a solar building technology competition initiated and sponsored by the U.S. Department of Energy since 2002 with universities around the world as participants. The competition aims at innovative research and utilization of renewable energy use and integrated solar design for residential buildings. It aims to explore how technology can be used to address the energy requirements of the 21st century and to promote the integration of green buildings with new technologies. The competition involves the fields of architecture, renewable energy, housing automation, Internet of Things, communications and media, and electric vehicles. The competition requires teams to design, build and operate a functional, comfortable, livable and sustainable residential building that uses solar energy as its single energy source by closely integrating solar energy, energy efficiency and architecture in a new and integrated way. The architectural proposals are evaluated through 10 indicators to select the best entries that integrate perfect design, smart energy, diverse innovation and marketing potential. The competition is known as the "Decathlon", as the final ranking is determined by 10 independent scoring systems through subjective expert evaluations and objective monitoring of all entries in terms of their architectural design, use of energy-saving strategies, regulation of the building's physical environment, and energy self-sufficiency.

In 2001, the organizers selected 14 college teams to participate in the first SD competition, and in September 2002, the teams transported their entries to the competition site in Washington, D.C., where they were built, exhibited, and evaluated over the period of 1 week. Since then, SD competitions have been held biennially in the United States. A total of 8 competitions have been held in the US since then, in 2005, 2007, 2009, 2011, 2013, 2015 and 2017 respectively.

In 2008, the Polytechnic University of Madrid and the Spanish Embassy in the United States introduced the Solar Decathlon to Europe. The Solar Decathlon Europe (SDE) was successfully held in Madrid (Spain), Versailles (France), and St. André (Hungary) in 2010, 2012, 2014, and 2019, respectively.

The first Solar Decathlon Africa (SDA) took place in September 2019 in the city of Ben Gouri, Morocco. The competition was in line with Morocco's goal of conceptualizing low-energy buildings to achieve net-zero energy buildings. To emphasize the importance of Decathlon Africa, participants must integrate regional sustainable raw materials while working on the various components of the building. The main goal of the competition was to build knowledge of net-zero energy buildings within the African continent, highlighting the advantages of decentralized solar energy in order to promote sustainable energy for all Africans.

China's first participation was in 2010 when Tianjin University and Tongji University took part in the European Solar Decathlon in Madrid, Spain. The SD competition in China began in 2011. On the afternoon of January 18, 2011, the National Energy Administration of China, Peking University, and the U.S. Department of Energy signed a Memorandum of Understanding (MOU) for cooperation in the Solar Decathlon in Washington, D.C., bringing the SD competition to China, marking the first time that the world's highest level SD competition has settled in Asia. The first and second Solar Decathlon China (SDC) were held in Datong, Shanxi Province in 2013 and in Dezhou, Shandong Province in 2018, respectively. It attracted a total of 58 universities from 19 countries and regions and was supported and participated by more than 570 related enterprises, more than 80 government-related departments, and more than 20 embassies and international institutions including the United States, France, Canada, Israel, and Denmark. It has attracted a total of 760,000 public visitors, received more than 500 government dignitaries, university leaders and business executives, and 300 multimedia issued more than 10,000 reports, spreading to an audience of 3 million people. 2021 China International Solar Decathlon was officially launched in September 2020 in Zhangjiakou City, Hebei Province, and 15 on-site finalist teams were identified in November of the same year.

In addition, the SD competition was also introduced to Latin America and the Middle East respectively, with two Solar Decathlon Latin America and Caribbean (SDLA) competitions and one Solar Decathlon Middle East (SDME) competition.

The SD competition has now expanded globally in the United States, China, Europe, the Middle East, Africa, and Latin America and the Caribbean. From 2002 to 2020, 18 competitions have been held.

The energy-efficient design strategies used in previous SD competition entries include both passive and active strategies. Passive energy-saving strategies are those that do not use active mechanical equipment, but rather use radiation, convection, and conduction to make heat flow naturally through the building and control the direction of heat flow through the performance of the building itself to obtain heating or cooling effects. Active energy saving strategy refers to the use of solar thermal, photovoltaic, and other controllable technologies for solar energy resources to achieve the collection, storage, and use of solar energy.

The design of a residential building starts with the use of simple and economical passive energy saving strategies for energy production and saving as much energy as possible. When passive energy-saving strategies do not meet the energy-saving requirements, active energy-saving strategies are applied. The active energy-saving technologies used in the SD competition include the design of HVAC systems, photovoltaic and hot water systems, lighting and equipment systems, intelligent systems, and other systems. Passive energy-saving strategies affect the overall form of the building to a greater extent.

4.3. Data Collecting and Screening

There are official websites for all previous SD competitions held in the US, Europe, China, Latin America, the Middle East, and Africa. The official website contains a record of all the processes and related documents of the competition from team recruitment to the official competition, including all the documents related to the competition rules and requirements as well as the project manuals and technical atlases related to the entries. As the official websites of the Solar Decathlon in China, Africa and Latin America are temporarily inaccessible. Therefore, the documents related to the 5 competitions of SDC2013, SDC2018, SDA2019, SDLA2015 and SDLA2019 and all the entries are not available. In addition, the files of the entries of the SD2002 and SD2005 competitions were missing from the official website of the U.S. Solar Decathlon and could not be obtained.

In this research stage, the competition rules and the project manuals and technical atlases of all the entries of all the previous competitions except the above 7 competitions were collected.

Data screening was performed to eliminate data with significant discrepancies or errors, which helped to improve data consistency. The screening principles are as follows:

By Building Stories

The majority of the competition's requirements for the number of stories are for single-story buildings. Also, multi-story buildings do not occupy a high proportion of the data set, so only single-story entries were retained.

By Building Forms

In the past years, according to the layout of the building form, it can be roughly divided into four categories: cluster, independent block, irregular and heterogeneous. When selecting the works, the cluster, irregular and heterogeneous categories were removed, and only the relatively regular works were kept, so as to facilitate the computer to learn and generate.

By Space Variability

Some of the entries in the SD competition were designed with variable space in order to improve space utilization. Since the functional zoning attributes of this type of space cannot be accurately defined, the entries containing flexible variable space and extremely flexible functional layout were screened out.

A total of 184 entries from 12 years of the SD competition were collected for this study. 98 entries were counted for the screened sample size, distributed as shown in Table 10. In total, 90 of the 98 cases were randomly selected as the training set, while the other 8 were selected as the testing set.

Table 10. Data Collected and Screened for Plan Generation.

Competition	Location	Entries	Retained
SD2007	Washington, DC, USA	20	15
SD2009	Washington, DC, USA	21	14
SD2011	Washington, DC, USA	19	13
SD2013	Irvine, CA, USA	19	16
SD2015	Irvine, CA, USA	15	11
SD2017	Irvine, CA, USA	11	9
SDE2010	Madrid, Spain	17	5
SDE2012	Madrid, Spain	18	8
SDE2014	Versailles, France	20	-
SDME2018	Dubai, UAE	14	7
SDE2019	St. André, Hungary	10	-
Total	-	184	98

4.4. Data Processing

4.4.1. Processing Principles

In order to ensure the consistency and comparability of training data and improve the training effect and generalization ability of SD-GAN. The following principles of sample processing were developed in this study:

Uniform Drawing

In the SD competition entries, different design teams used different drawing tools, drawing styles, and drawing standards. To ensure the consistency of the training samples, the cartography needs to be uniformly processed so that they have similar styles, formats, and standards. This can reduce the generalization problem of SD-GAN under different mapping styles and improve its adaptability to new samples.

Uniform Annotation

In SD-GAN samples, annotation refers to the marking or annotation of building elements (e.g., walls, windows, doors, etc.) or other regions of interest. The purpose of uniform annotation is to ensure that consistent annotation methods and annotation rules are used for the same type of building elements or regions. This can avoid SD-GAN's confusion about different annotation methods and improve its understanding of tagging accuracy and consistency.

Uniform Labeling

By unifying the labeling forms such as size, dimensions and pixels of training samples, the variability of input data can be reduced, and the training effect and generalization ability of SD-GAN can be improved. In this way, it can better learn the common features of images without focusing too much on the subtle differences between samples. This is particularly important for deep learning tasks in architectural design solutions, as it ensures that the model is able to make accurate predictions and analysis for building images at different scales.

4.4.2. Plan Generation Samples

Uniform Drawings

Redraw each entry's architectural plans and unify the overall furniture style, doors, and windows of the drawings. Each functional space was characterized by specific furniture.

Uniform Annotation

The screened entries had a relatively similar functional layout, with a living room, dining area, kitchen, one or two bedrooms, study or workspace, bathrooms, and equipment rooms. According to the annotation principle (Table 11), the FSL corresponding to the floor plan of each entry was first created. Then, the building area was filled with black to generate the BEP, as shown in Figure 37.

Table 11. Annotation Principle for FSL.

Name	Color	Value (R, G, B)
Corridor		255, 0, 0
Bedroom		0, 255, 0
Living Room		0, 0, 255
Kitchen		255, 255, 0
Dining Room		255, 0, 255
Bathroom		0, 255, 255
Equipment		128, 128, 128
Workspace		0, 0, 128
Window		128, 0, 0
Door		0, 128, 0

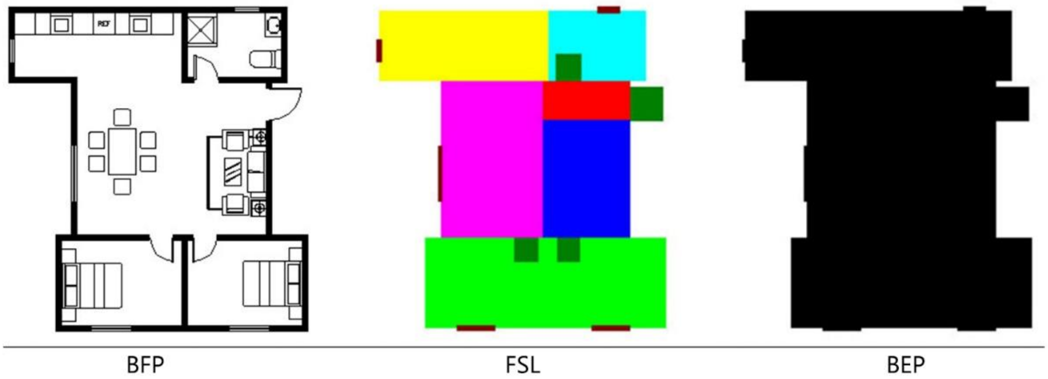


Figure 37. Data Processed Result Demonstration.

Uniform Labeling

Each individual image in the label has a size range of 256 × 256 pixels, and the label canvas size is 90 mm × 180 mm with a resolution of 72 ppi. As shown in Figure 38 and Figure 39, this study requires two separate labels: one with FSL and BEP placed on the left and right sides and the other with BFP and FSL placed on the left and right sides.

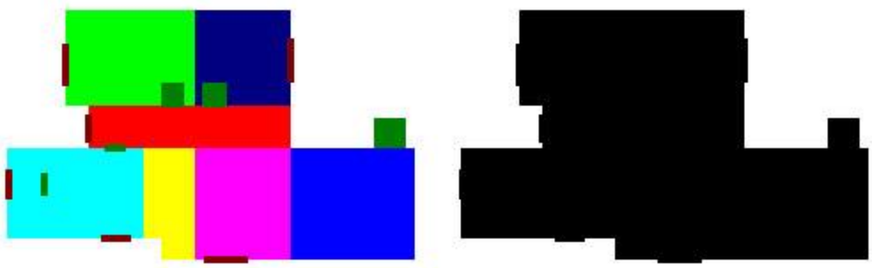


Figure 38. Model 1 Label Demonstration.

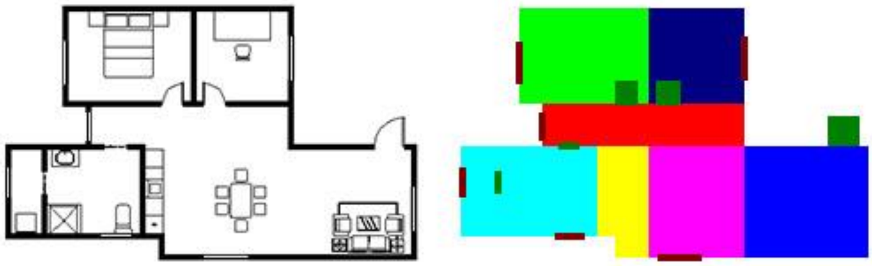


Figure 39. Model 2 Label Demonstration.

4.4.3. Façade Generation Samples

Unfolding Façades

Unlike the building plan, the unfolding process is required to unfold the building façade from a three-dimensional form into a two-dimensional plan, similar to unfolding a piece of paper. This is done for several reasons:

- Model Requirements

The SD-GAN network is set up to handle data in a two-dimensional plan, and it is only by unfolding a sample of the building façade that it can perform tasks such as classification, identification, and segmentation on it.

- Visualization Analysis

The unfolded building façade can show the various elements and details of the building, including walls, windows, doors, etc., in a more visual way. This makes it easier for SD-GAN to observe and analyze features such as the structure, scale, and shape of the building to make more accurate assessments and decisions.

- Feature Extraction

The feature extraction can be more easily performed on the building façade after the unfolding process. Various features of the building façade, such as edges, textures, colors, etc., can be more easily analyzed and decided on a two-dimensional plan for further analysis.

Processing Differences

- Higher Resolution

This study first analyzed and filtered the SD entries, using a variety of façade segmentation layouts (the same role as the previous FSL, here also referred to as FSL) as labels for the data, and used this to further process the data. An example of a standard format data set is shown in Figure 40. The image is 256 pixels high, 512 pixels wide. The image on the left side is a labeled FSL of low-rise housing and the right side is the building exterior profile (the same role as the previous BEP) of the labeled one. The difference was that considering the complexity of the building façade components, it was necessary to increase the resolution of the samples to facilitate the learning of SD-GAN. Therefore, the label resolution for this stage was set to 300 dpi.

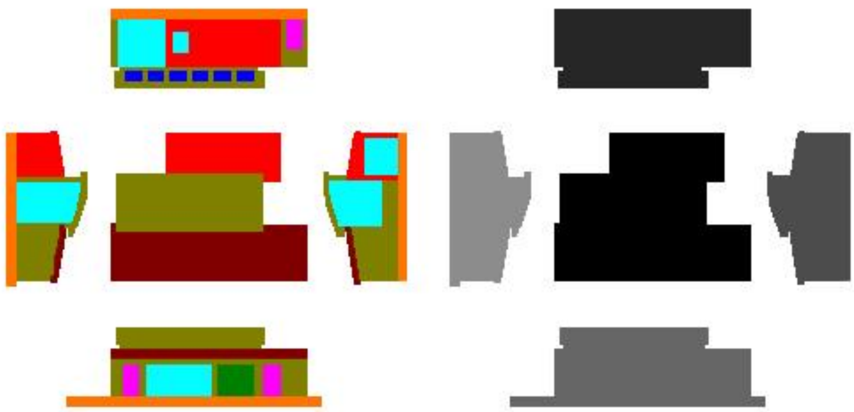


Figure 40. Label Demonstration for Façade Generation.

- Orientation Annotation

The orientation of a house affects the energy efficiency of a building by influencing its performance in terms of lighting, ventilation, heating, and cooling. For example, if a house is oriented to the south, it will receive more sunlight in winter, thus reducing heating energy consumption, and it will be able to avoid excessive sunlight in summer to keep the house cooler. On the contrary, if the house front faces north, additional energy consumption such as heating and lighting is required to maintain the temperature and brightness of the interior. Therefore, when designing a building, the orientation of the house should be considered comprehensively according to the local climatic conditions and the location of the building, etc., in order to achieve the energy saving effect of the building in an optimal way.

However, the traditional black block cannot determine the orientation of the façade when processing the BEP, the effect of orientation on the generation of the façade cannot be recognized when the generation is carrying it out. Therefore, this research discarded the usual black block diagram when producing the data set and instead applied different transparency borders to the façades of different orientations: 85% RGB (0, 0, 0) for north-facing façades, 70% RGB (0, 0, 0) for east-facing façades, 60% RGB (0, 0, 0) for south-facing façades, 45% RGB (0, 0, 0) for west-facing façades RGB (0, 0, 0) for the west-facing façade , and 100% RGB (0, 0, 0) for the roof.

- Highlighting Features

Building façade features play a key role in the training sample for façade generation of solar competition entries in the following areas:

Energy Efficiency and Collection Efficiency: Attention to features such as solar panel placement, window design, and shadow analysis ensures that the building façade performs optimally in terms of energy collection efficiency. Proper placement and design can maximize solar energy capture and utilization and improve overall energy efficiency.

Building Appearance and Appeal: As the exterior display of a building, features such as material selection, color and texture are critical to the overall appearance and appeal of the building. Focusing on these features ensures that the solar system is in harmony with the building's exterior, making the solar equipment visually pleasing and seamlessly integrated.

Comfort and Indoor Environmental Quality: Attention to features such as windows, openings, and insulation can affect the quality and comfort of the indoor environment inside the building. Proper design can provide natural light and ventilation, reduce heat loss and heat build-up, improve the indoor environment, and provide a more comfortable living experience for occupants.

Therefore, in the façade annotation, the following features need to be focused on:

Photovoltaic Panels: Focus on the layout of photovoltaic panels on the building façade, including area, quantity, orientation and angle. These features have a significant impact on the energy collection efficiency of the solar system.

Windows and Openings: Focus on the location, size and type of windows and other openings in the building façade. Properly designed windows provide natural light and ventilation that work in conjunction with the placement of the solar system to maximize energy efficiency.

Building Materials and Appearance: Focus on the types of materials used in the building façade. The right choice of materials can improve the attractiveness of the building's appearance, while also considering the feasibility of integration with solar systems and the potential for improving the building's energy efficiency.

For the above features, each component in the label production has its corresponding RGB color, with the detailed color settings shown in Table 12.

Table 12. Annotation Principle for Components.

Name	Color	Value (R, G, B)
Photovoltaic Panels		128, 0, 0
Plain Walls		128, 128, 0
Greening		0, 128, 0
Door		255, 0, 255
Timber Walls		255, 0, 0
Railings		255, 255, 0
Windows		0, 255, 255
High Windows		0, 0, 255
Steps		255, 115, 0

4.5. Summary

Accurate and effective labeling will significantly improve the training effect of SD-GAN and save a lot of training time.

This chapter provides an overview of the origins and development of the SD competition. The energy-saving features of the entries are briefly introduced in terms of volume design, space organization, natural ventilation and lighting, and design of thermal buffer space. Through screening, 98 entries were selected as the training data for SD-GAN. 90 of the entries were used as the training set, while the other 8 were used as the test set.

In terms of data processing, this chapter describes the image pair label processing methods for plan and façade generation, respectively. Among the labels for the façade generation model training, the labeling scheme for the corresponding orientation degrees of the 5 façades of the building is particularly considered to fully consider the influence of orientation on the building and to obtain more accurate training results.

Chapter 5. Preliminary Training and Data Augmentation

5.1. Introduction

Based on the SD-GAN network architecture described in Chapter 3 above, this chapter will conduct preliminary model training and test the model validity and generative capability through the building plan generation task. The whole research process is divided into three main steps: training, testing and evaluation.

In the training phase, the building floor plan data prepared in Chapter 4 above will be used for training to enable SD-GAN to obtain the capability of generating building floor plans. In the testing phase, the SD-GAN will be tested for generation with the testing dataset to generate FSL and BFP, respectively.

In the validation phase, the generation results will be compared with real data to evaluate the strengths and weaknesses of the SD-GAN generation capabilities. The evaluation will be implemented for several aspects, including different feature dimensions such as clarity of spatial assignment (CSA), reasonableness of function distribution (RFD), clarity of color block boundaries (CCB), wall generation accuracy (WGA), and furniture generation accuracy (FGA). The evaluation and comparison of the generated results of the preliminary training model can provide a more comprehensive understanding of the performance and limitations of SD-GAN in the building floor plan generation task.

When unsatisfactory preliminary training occurs, targeted data augmentation will be performed to improve the accuracy of the training results.

For higher demanding generative models such as SD-GAN, the explicit requirement for data augmentation is more stringent. In this chapter, a geometric transformation method will be used to perform data augmentation on 90 data training sets, including rotate and flip operations, which can generate a series of new data samples and help the model better adapt to the sample data.

It is hoped that the results of this chapter will find a method that is most suitable for efficient training of small sample networks, explore the strategies and implementations of data augmentation, and provide more means and methods for subsequent research and development.

5.2. Preliminary Plan Training

5.2.1. Training Method

The generator and the discriminator will be called simultaneously during network training. Using cross-entropy loss, which is commonly used for binary classification, the loss function measures the loss of true and false classification on each corresponding image chunk of the discriminator.

The Adam optimizer is used to optimize the network with the momentum parameter set to 0.5. The learning rate is set to 0.0002 empirically. An epoch in training indicates that all the data are fed into the network for one forward calculation and back propagation, i.e., the model completes one whole learning cycle for all samples. The epoch is set to 400 in the preliminary training to achieve a better fit (better learning effect).

Both sub-models of SD-GAN are operated using the same 2 steps as shown in Figure 41 and Figure 42:

1. The processed training set is fed into SD-GAN for the training step. Model 1 takes BEP as input to output colored FSL. Model 2 takes FSL as input and produces BFP. The output will become closer to the real data as the generator and discriminator evolve simultaneously.

2. The testing dataset is used to test the capability of SD-GAN once the generator and discriminator have converged to an equilibrium state. The BEP of the test set can be input, and then the output generated results can be visually compared to the original image.

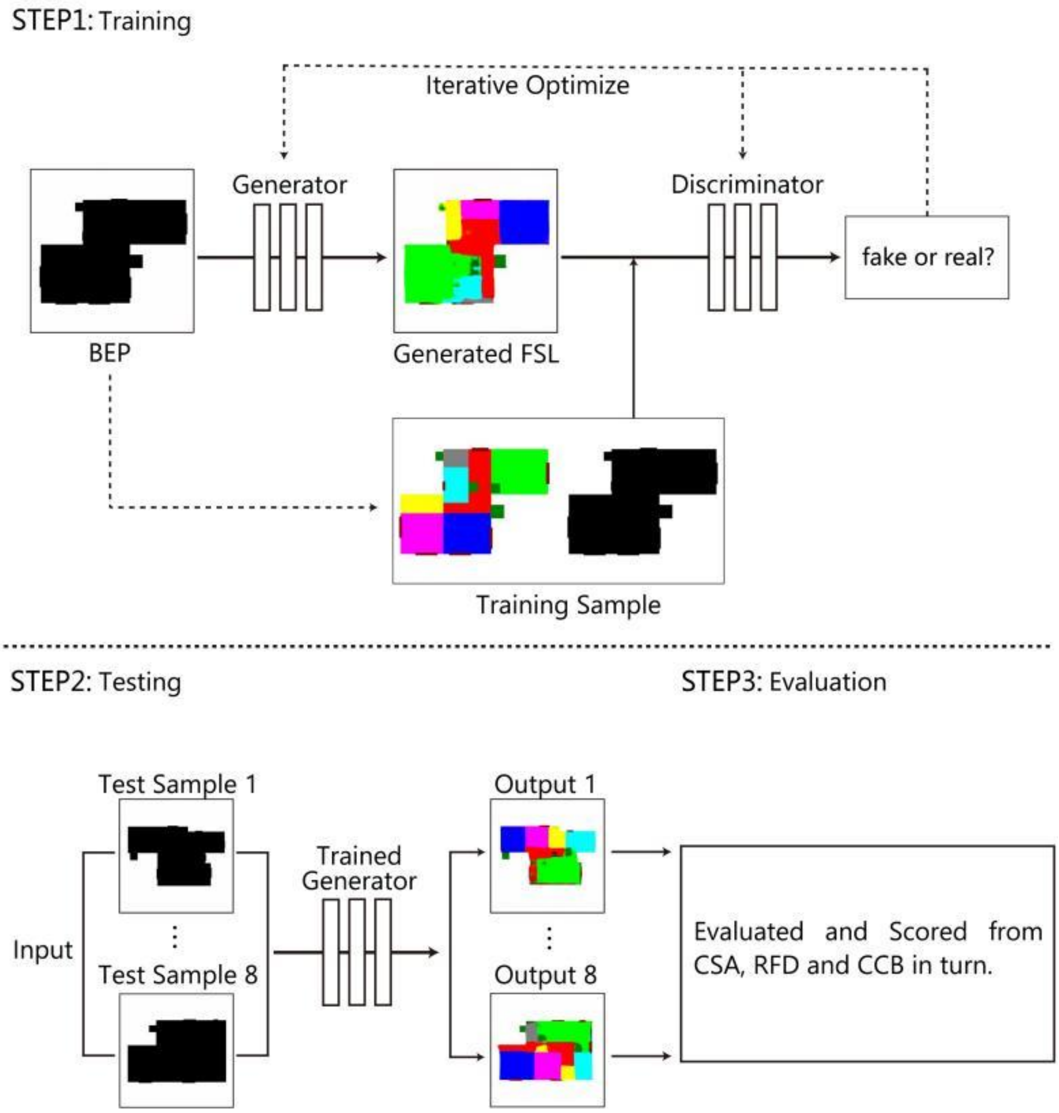


Figure 41. Model 1 Training and Testing Flow.

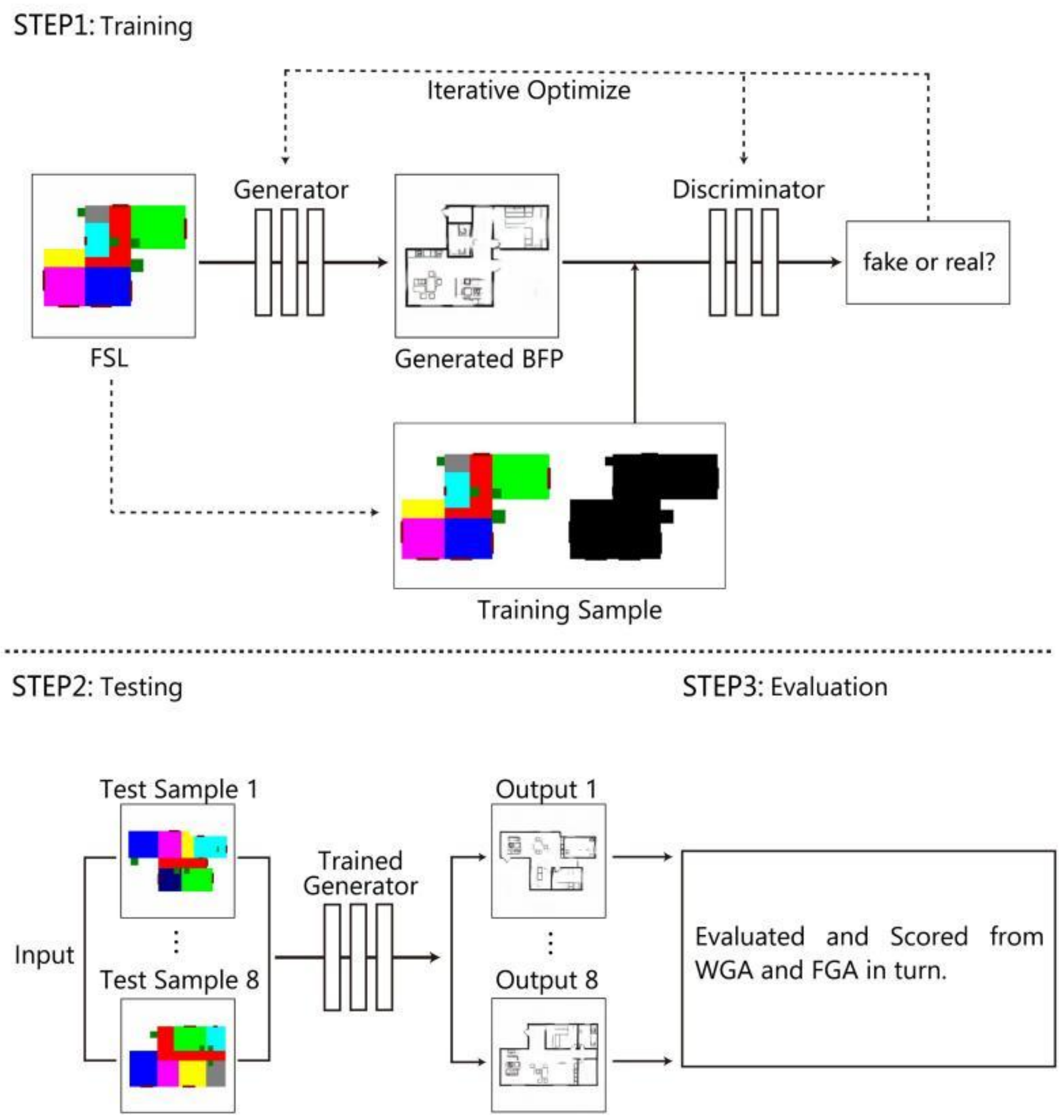
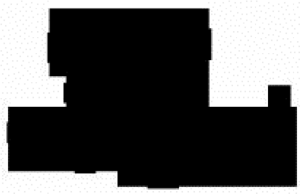
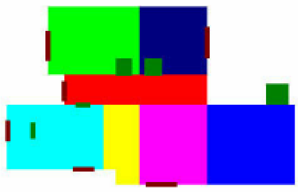
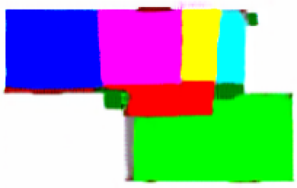
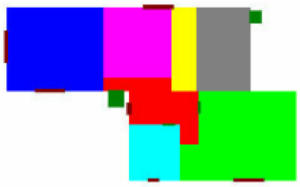
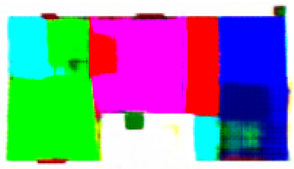
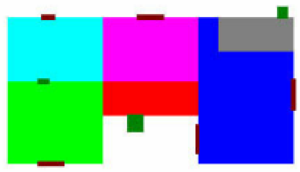
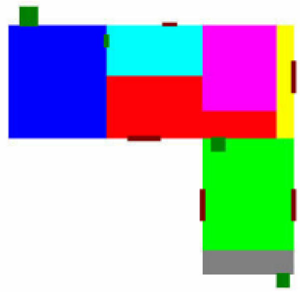
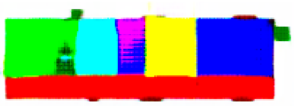
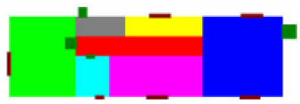


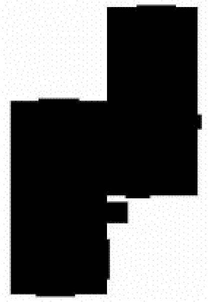
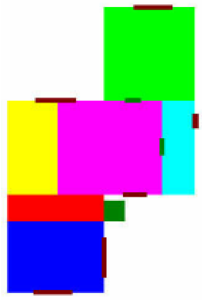
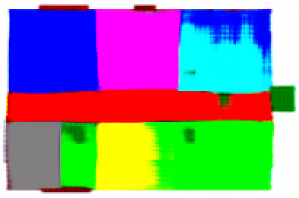
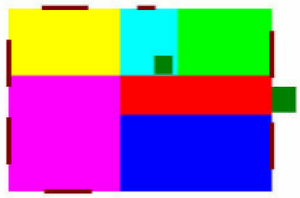
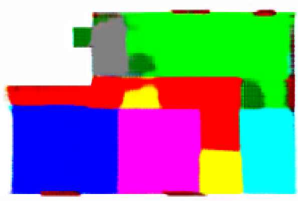
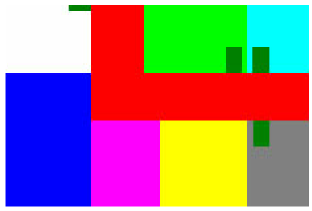
Figure 42. Model 2 Training and Testing Flow.

5.2.2. Training Results

As mentioned in Section 4.2 above, the training results of Model 1 were tested by 8 testing samples. The inputs are the BEPs, the ground truths are the original FSLs of the testing samples, and the outputs are the prediction results of Model 1 (Table 13). The training results of Model 2 are also tested by 8 testing samples. The inputs are FSLs, the ground truths are the original BFPs of the testing samples, and the outputs are the prediction results of Model 2 (Table 14).

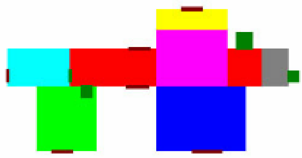
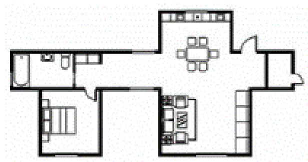
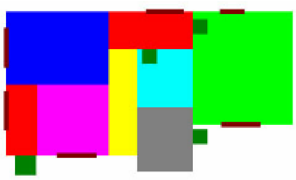
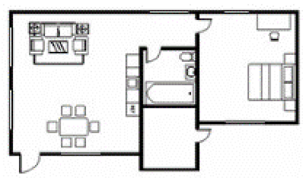
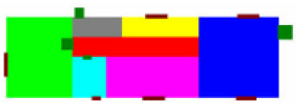
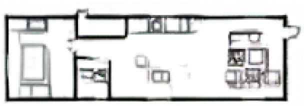
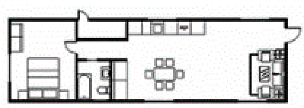
Table 13. Testing Results of Models 1.

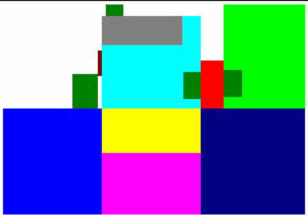
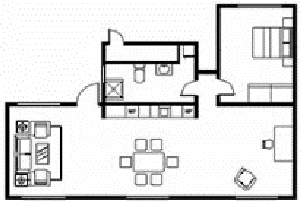
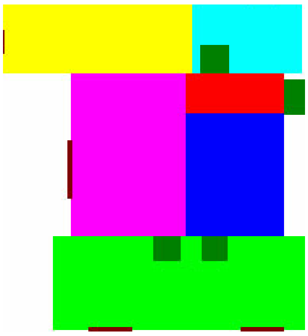
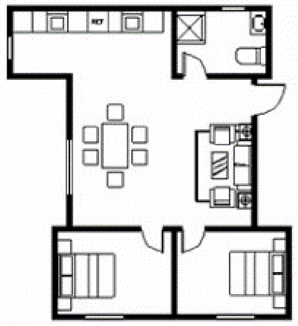
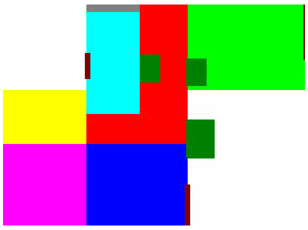
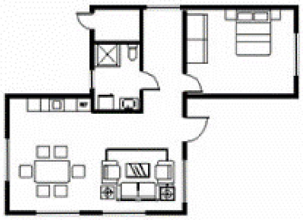
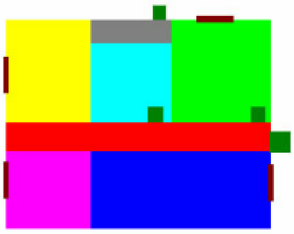
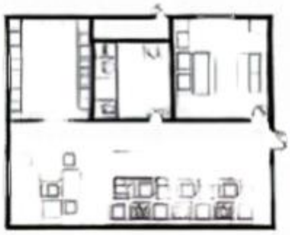
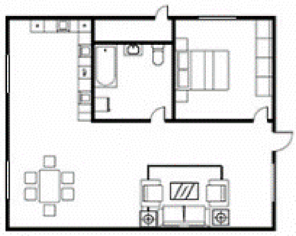
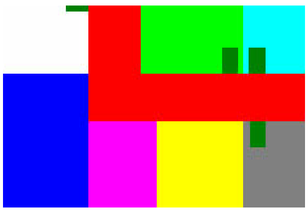
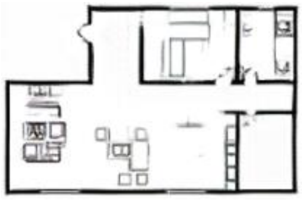
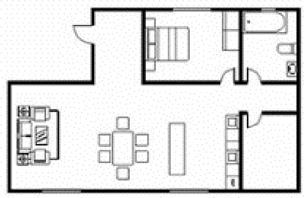
No.	Model 1		
	Input	Output	Ground Truth
07-06			
07-09			
09-02			
09-14			
09-15			

No.	Model 1 Input	Model 1 Output	Model 1 Ground Truth
12-04			
12-14			
18-01			

corridor; dining room; bedroom; bathroom; living Room; equipment; kitchen; workspace; window; door.

Table 14. Testing Results of Models 2.

No.	Model 2 Input	Model 2 Output	Model 2 Ground Truth
07-01			
12-03			
09-15			

No.	Model 2		
	Input	Output	Ground Truth
13-11			
15-08			
17-06			
12-14			
18-01			

corridor; dining room; bedroom; bathroom; living Room; equipment;
kitchen; workspace; window; door.

5.3. Preliminary Plan Training Evaluation

5.3.1. Evaluation Method

The clarity and functional rationality of the generated results are the assessment points of Model 1; the accuracy of wall generation and the rationality of furniture distribution are the evaluation focus of Model 2.

The quantitative scoring method is used for the outcome assessment step. The generated results of Model 1 are evaluated and scored from the CSA, RFD, and CCB in turn (unacceptable: 0; bad: 1; not bad: 2; acceptable: 3; good: 4; very good: 5). The generated results of Model 2 are evaluated and scored from the WGA and FGA in turn (unacceptable: 0; bad: 1; not bad: 2; acceptable: 3; good: 4; very good: 5).

5.3.2. Evaluation Results and Discussion

The test results of Model 1 were evaluated in terms of CAS, RFD, and CCB and scored using the score scale indicated before. The test results of Model 2 were evaluated in terms of WGA and FGA. Table 15 shows the outcome of the evaluation. Graphical analysis is performed in Figure 43.

Table 15. Preliminary Evaluation of Model 1 and Model 2.

No.	Model 1			No.	Model 2	
	CSA	RFD	CCB		WGA	FGA
07-06	3	2	2	07-01	5	4
07-09	4	3	3	12-03	5	5
09-02	1	1	2	13-11	5	4
09-14	4	3	3	15-08	4	5
09-15	1	1	2	09-15	5	4
12-04	1	1	1	17-06	5	4
12-14	2	2	2	12-14	5	4

No.	Model 1			No.	Model 2	
	CSA	RFD	CCB		WGA	FGA
18-01	2	2	3	18-01	5	5
Median	2	2	2	Median	5	4
Mean	2.25	1.875	2.25	Mean	4.875	4.375
STDEV	1.2	0.78	0.66	STDEV	0.33	0.48

The majority of the Model 1 results were not clear enough for CSA (mean: 2.25, Median: 2), CCB (mean: 2.25, Median: 2), or not reasonable enough for RFD (mean: 1.875, Median: 2). The level of performance stability was insufficient (STDEV: CSA 1.2, RFD 0.78, CCB 0.66). It is more critical to generate a clear and explicit FSL first in order to generate a reasonable and complete building plan. Model 1's training had to be improved further.

The overall results of Model 2 reveal that the BFP generated from the FSL based on 90 training samples can basically satisfy the requirements, and the generated positions of walls (score: 4.875, Median: 5) and furniture (score: 4.375, Median: 4) are more accurate, which can accurately represent the functions of each space. The performance is also much more stable (STDEV: WGA 0.33, FGA 0.48).

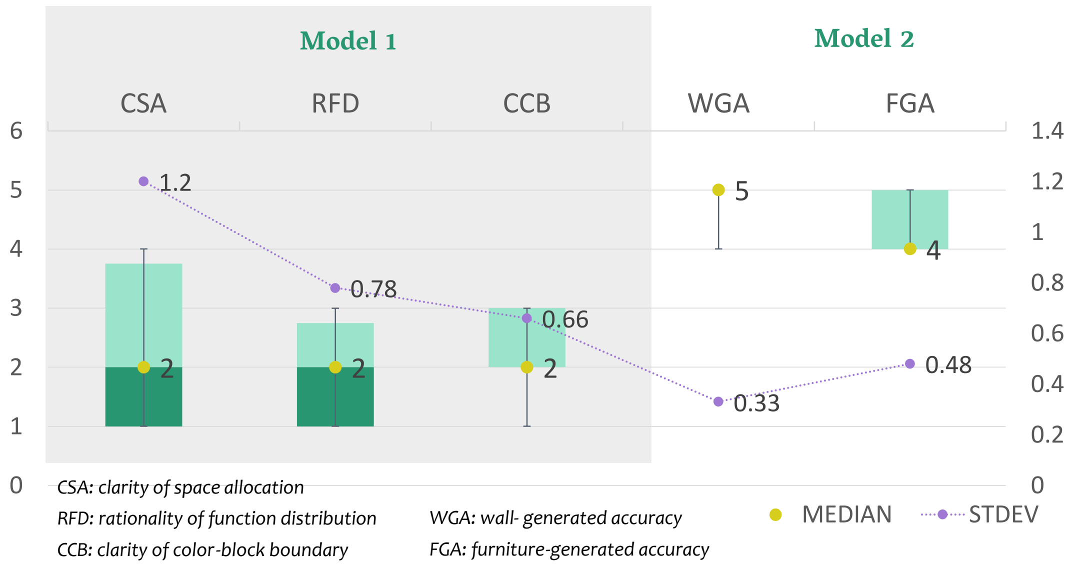


Figure 43. Chart Analysis of the Preliminary Evaluation Results.

The main reason for the unsatisfactory results generated by Model 1 may be that the mapping relationships between BEP and FSL are often highly complex and diverse. Each SD competition entry has unique design requirements and functional needs, so there may be great variations and differences between samples. This in turn makes it difficult for the SD-GAN learning algorithm to accurately capture relevant information, resulting in its low generalization capability.

However, with limited SD competition entries, obtaining a large amount of high-quality data is a challenge that must be addressed. The limited samples and unbalanced distribution may lead to the inability of SD-GAN to adequately learn complex mapping relationships.

Therefore, there is a need to expand the existing dataset by data augmentation techniques to generate more variable samples of BEP and FSL.

5.4. Data Augmentation and Training

5.4.1. Data Augmentation Method

In order to achieve a better model trained based on the existing data of the SD competition and improve the generated results, this study adopts the data augmentation method to expand the existing training samples of Model 1.

In order to avoid affecting the normal scale and proportion of the BFP and not to change the color distribution of the FSL, we adopted the geometric transformation method to expand the existing training samples to improve the training performance of Model 1 (unsatisfactory training result, see section 5.3 above). The 90 training samples of Model 1 were flipped vertically and horizontally, rotated 90° both clockwise and counterclockwise, and rotated 180°, without modifying the scale, the proportion of the building layout, or the color distribution of FSL, as shown in Figure 44. The expanded training sample data set comprised a total of 400 labels after augmentation.

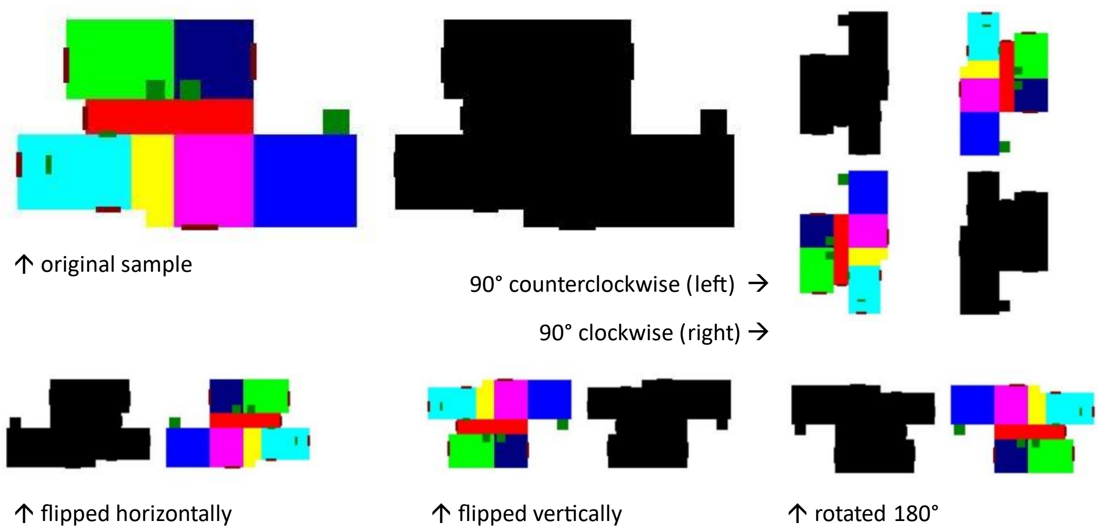
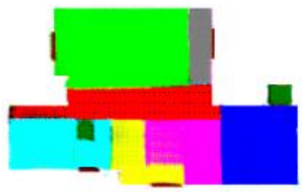
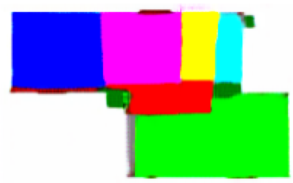
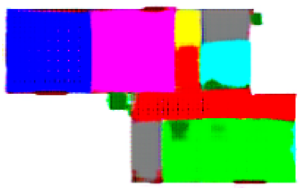
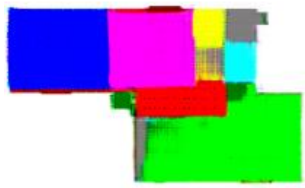
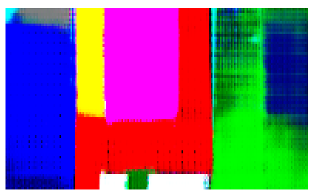
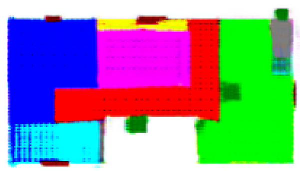
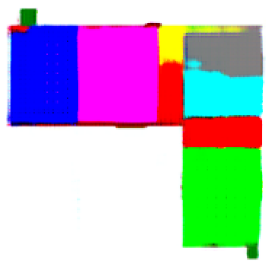
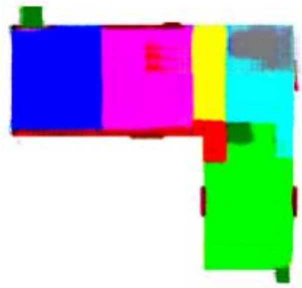
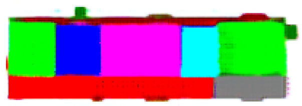
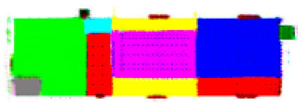


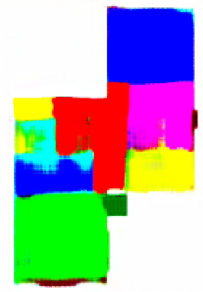
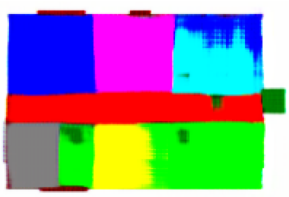
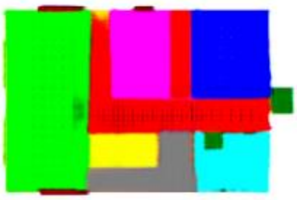
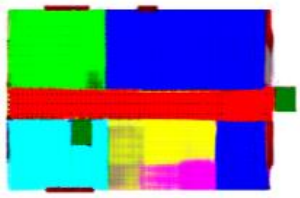
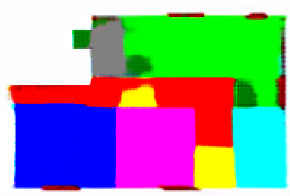
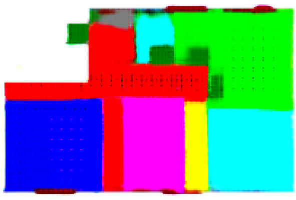
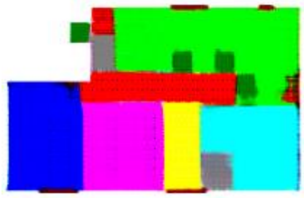
Figure 44. Geometric Transformation Flow.

5.4.2. Augmented Training Results

To compare the performance of different numbers of training samples on the generated results, 240 and 400 samples were selected for training Model 1-1 and Model 1-2 with same steps mentioned in section 5.2 above, respectively. Both of them were set with 200 epochs. Models 1-1 and 1-2 were tested independently with the same 8 testing samples (Table 16) and evaluated according to the same criteria as section 5.3 above.

Table 16. Testing Results Comparison

No.	Model 1	Model 1-1	Model 1-2
07-06			
07-09			
09-02			
09-14			
09-15			

No.	Model 1	Model 1-1	Model 1-2
12-04			
12-14			
18-01			

corridor; dining room; bedroom; bathroom; living Room; equipment;
kitchen; workspace; window; door.

5.5. Augmented Training Evaluation

5.5.1. Evaluation Results

Following the evaluation method mentioned in section 5.3.1 above, comparison results (Table 17) show that the results of Model 1-1 with 240 training samples and 200 epochs have no significant improvement compared with Model 1. There are still problems of unclear CSA, CCB, and unreasonable RFD with unstable performance. Model 1-2 with 400 training samples and 200 epochs shows significant improvement compared to Models 1 and 1-1, with clear and complete CSA (score: 4.875), CCB (score: 4.25), and reasonable RFD (score: 4.625), as well as stable performance in all aspects. This demonstrates the feasibility of enhancing learning ability by expanding the data set through the geometric transformation method.

Table 17. Testing Evaluation of Model 1-1 And Model 1-2.

No.	Model 1-1			Model 1-2		
	CSA	RFD	CCB	CSA	RFD	CCB
07-06	1	1	1	5	4	5
07-09	3	2	4	4	5	4
09-02	2	2	2	5	5	4
09-14	1	2	3	5	5	4
09-15	3	2	3	5	5	5
12-04	1	1	2	5	5	4
12-14	4	2	4	5	5	4
18-01	3	2	3	5	3	4
Median	2.5	2	3	5	5	4
Mean	2.25	1.75	2.75	4.875	4.625	4.25
STDEV	1.09	0.43	0.97	0.33	0.7	0.43

5.5.2. Discussion

The evaluation results are collated and analyzed graphically by in Figure 45. It can be clearly observed that the different generative performance of the 2 different data augmented sample sizes is very obvious. Model 1-1 contains only 270 samples and the generative ability after training is not much different from that of Model 1. This indicates that although the sample size is expanded through data augmentation techniques, the models are still limited by the data during training due to the limited number of original samples, and thus the performance may be relatively consistent.

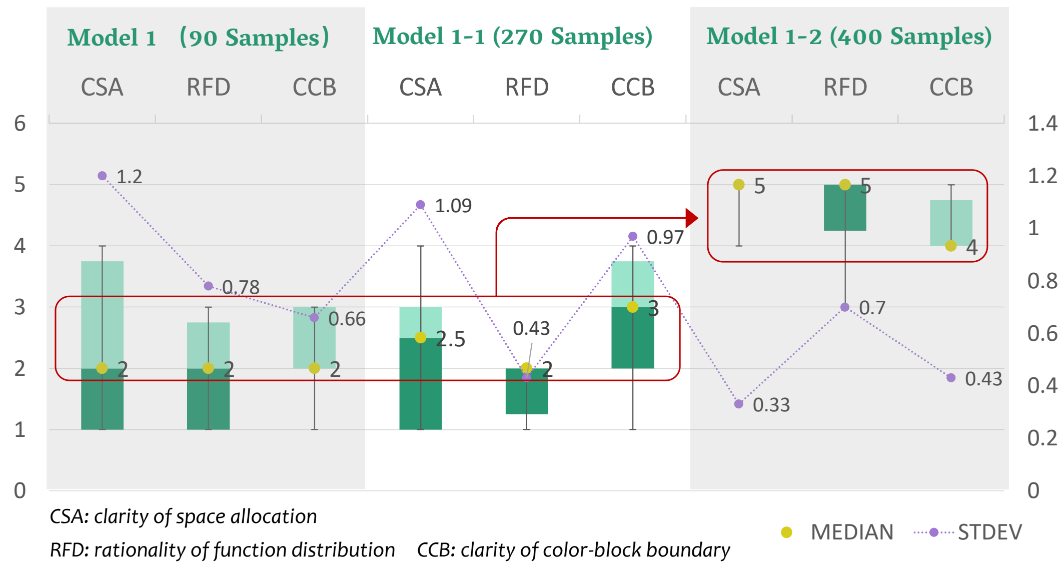


Figure 45. Chart Analysis of the Augmented Evaluation Results.

However, when the number of samples is increased to 400, Models 1-2 have more samples for learning and training. This allows SD-GAN to better understand and capture the BEP to FSL mapping relationship and improve its prediction performance. More samples provide more variation and diversity, allowing the model to learn patterns and regularities in the data more comprehensively.

At the same time, it is important to note that despite the high mean and median values of the metrics, the RFD performance of Model 1-2 is still relatively unstable, with an STDEV of 0.77. The reason for this is the low RFD value due to the presence of equipment obstructing traffic in the generated results of the 18-01 testing sample. This situation occurred once in 8 tests. It needs to be noted in future SD-GAN applications.

5.6. Summary

This chapter first introduces the preliminary training process of SD-GAN and describes the differences between Model 1 and Model 2. Model 1 mainly focuses on the generation of FSL, which needs to be evaluated in three aspects: spatial allocation, functional distribution and edge clarity of the generated results; Model 2 mainly focuses on the generation of BFP, which needs to be evaluated in two aspects: wall and furniture generation accuracy.

After preliminary training, the mean value of CSA and CCB of Model 1 are only 2.25, and the value of RFD is even lower at 1.875, which indicates that the learning ability of SD-GAN is limited in such small sample training if the mapping relationship of image pairs is complex or not clear enough.

The performance of Model 2 is much better than that of Model 1, with a high WGA of 4.875 and a high FGA of 4.375. This indicates that SD-GAN can still perform quite well for image pairs with relatively simple mapping relationships. However, in real datasets, the mapping relationships of image pairs are often complex or not clear enough, so corresponding data augmentation process is needed to improve the generalization ability of SD-GAN.

After that, this study conducts experiments on data augmentation for the case of unsatisfactory performance of SD-GAN with small sample training. By applying the geometric transformation method, data augmentation was performed on a training set of 90 samples in order to improve the generalization ability and robustness of the model.

In a comparative analysis of the experiment data, the performance of the 3 models (1, 1-1, 1-2) was compared over 200 epochs. The results show that by training with more training data (400 samples) after augmentation, Models 1-2 achieved significant performance improvements with scores of CSA (4.875), CCB (4.25) and reasonable RFD (4.625), respectively, and a large improvement in stability.

Overall, Model 2 performs significantly better than Model 1 even with small sample training. This may be because the image mapping relationship between FSL and BFP is clear and easy to understand, indicating that Model 2 relies more on experience and regularity. In contrast, the mapping relationship between BEP and FSL is vague, which means that the generation of FSL relies more on creativity after summarizing the experience compared with the generation of BFP, which is the intelligent side shown by SD-GAN.

The experiment results in this phase show that the training of generative models such as SD-GAN using data augmentation methods can improve the performance and accuracy of the models to a certain extent.

At the same time, it cannot be ignored that there is still a risk that the generated results do not meet the design requirements and require human correction (i.e., the human-AI collaborative design process). This likewise demonstrates the risk that SD-GAN performs even more poorly when dealing with façade generation tasks where the BEP is fragmented, and the building components are more complex in form and layout. Further enhancement of its generative capabilities is needed.

Chapter 6. Generator Replacement

6.1. Introduction

To achieve efficient use of energy and reduce waste, modern efficient residential buildings often employ various active and passive technologies. These techniques interact with various factors such as building volume and orientation, and more uncertain endogenous factors can bring some confusion to the learning of SD-GAN, making the generation results more dependent on creative performance. Therefore, the task of building façade generation is more challenging for SD-GAN.

In Chapter 5 above, the experiments on building plan generation revealed that SD-GAN performed unstable in the face of more complex image mapping relationships. Although the problem has been improved to some extent by data augmentation methods. However, more complex building façade generation tasks may be a dilemma for SD-GAN again.

Based on the above considerations, this chapter will first conduct a preliminary experiment on SD-GAN for building façade generation. If the results are unsatisfactory, the experiment will focus on the generator replacement of SD-GAN. The experiment will replace the generators of the original U-net structure with U-net++, HRNet and AttU-net, which have different perceptual capabilities, respectively, in order to compare the generation performance of different generators for complex information images.

To provide a more comprehensive evaluation of the generation results, a combination of subjective and objective evaluation methods will be used. The method will be subjectively evaluated by a targeted questionnaire. The objective evaluation will be performed with the help of a graph structure similarity model. Finally, the results of the subjective and objective evaluations will be analyzed comprehensively in order to determine the best generator structure to cope with different scenarios.

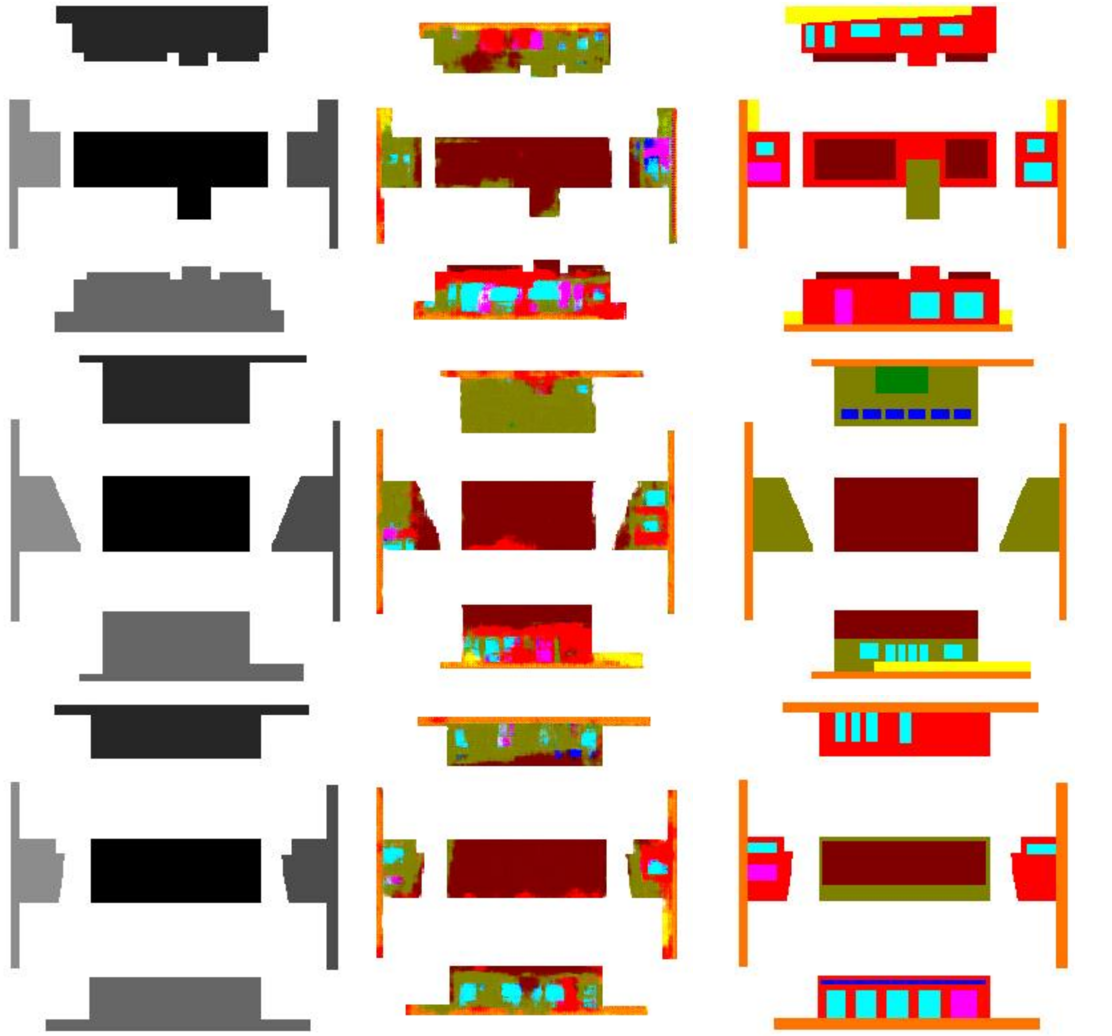
Overall, the task of this chapter is to perform a multiple scenario comparison of SD-GAN's generators to ensure that it shows better generative performance in the façade generation phase. At the same time, it is hoped that this training-evaluation process can provide some methodological reference for future refinement of human-AI collaborative design tools.

6.2. Preliminary Façade Training

The experiment of SD-GAN generation under the original generator is performed first. Table 18 shows the results generated using the U-net network with a learning rate set to 0.0002 and a number of iterations of 400. The input to the model is the building façade boundary image (BEP), the training Ground Truth is the building façade layout color block image, and the output is the output building façade layout color block image (FSL), taking a total of 2.5 h.

Table 18. Generating Results by Using The U-net Network.

Input	Output	Ground Truth



Photovoltaic Panels; Plain Walls; Greening; Door; Timber Walls;
Railings; Windows; High Windows; Steps.

By observing the experiment results, it can be found that the original generator of SD-GAN does perform poorly. It is mainly manifested in the following points:

- Most of the generated building components are not complete enough, and several components appear to be mixed together. This indicates the hesitation of SD-GAN in the generation process.
- The edges of the relatively shaped generated building components are not clear and do not match the morphological features of the components. This indicates that SD-GAN has not fully learned the morphological features of the building components.
- The generated FSL images are heavily cluttered, which may have an impact on further recognition.

In general, there are 3 possible reasons for the above problems:

- The existing network architecture has a learning and generation bottleneck, and the network architecture needs to be adjusted.
- The training process needs to be optimized.
- Insufficient consistency of the dataset and the influence of image noise.

Since a uniformly produced dataset is used, the last factor regarding the dataset can be excluded. In the following, further experiments are needed to address the first two issues.

6.3. Generator Replacement Training

Same as section 5.2 above, the entries of the SD competition were collected at the beginning. All the building façades were processed to obtain a comprehensive data set for training and testing. A series of façade generation models were built based on the SD-GAN neural network, re-placing the U-net generative network with U-net++, HRNet and AttU-net respectively. After training, the results of multiple sets of experiments were evaluated from both subjective and objective aspects (Figure 46).

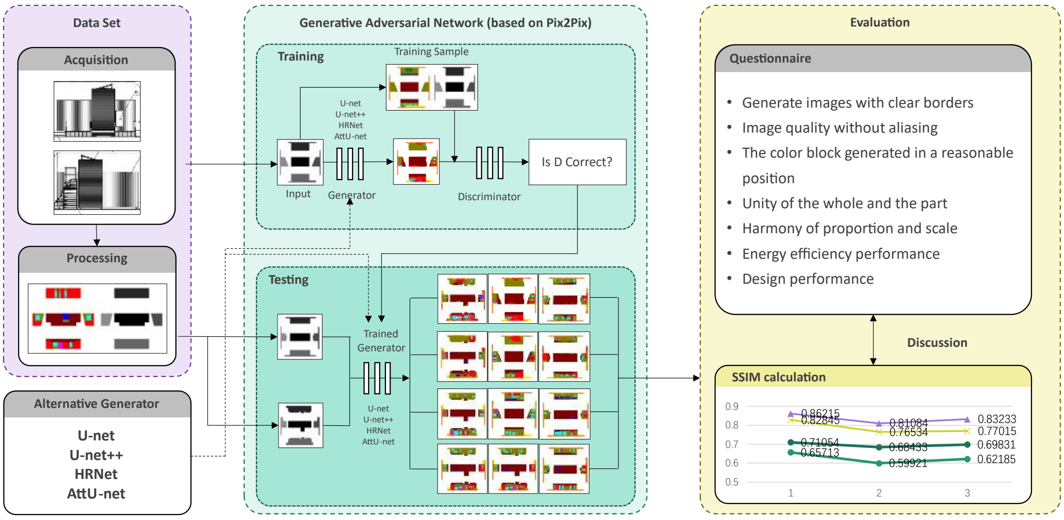


Figure 46. Research Framework.

6.3.1. Generator Brief

U-net Network

The U-net network structure is based on the Encoder-Decoder convolution and deconvolution operations(140). As well, the Encoder-Decoder based model is modified by adding a skip-connection, so that the left and right sides of the structure are directly connected, and layer i is directly connected to layer $n-i$, thus mapping the encoder output. The aim of the convolution process is to convolute the image to the right. The purpose of the convolution process is to extract the image features and compress the image, while the purpose of the deconvolution process is to up-sample the image size to achieve the original resolution.

The U-net generative network used in this study is set up with 5 layers of convolution and 5 layers of deconvolution, and the network structure of the U-net is shown in Figure 47. The padding of all five layers is set to 1. The deconvolution layers are also up sampled using a 3 × 3 convolution kernel and a 2 × 2 deconvolution, and the padding of all five deconvolution layers is set to 1. The input of each deconvolution layer in the generative network structure includes both the output of the previous layer and the output of the corresponding convolution layer. The input to each layer of the generative network structure includes the output of the previous layer and the corresponding convolution layer, so that the generated image retains as much information as possible from the original image.

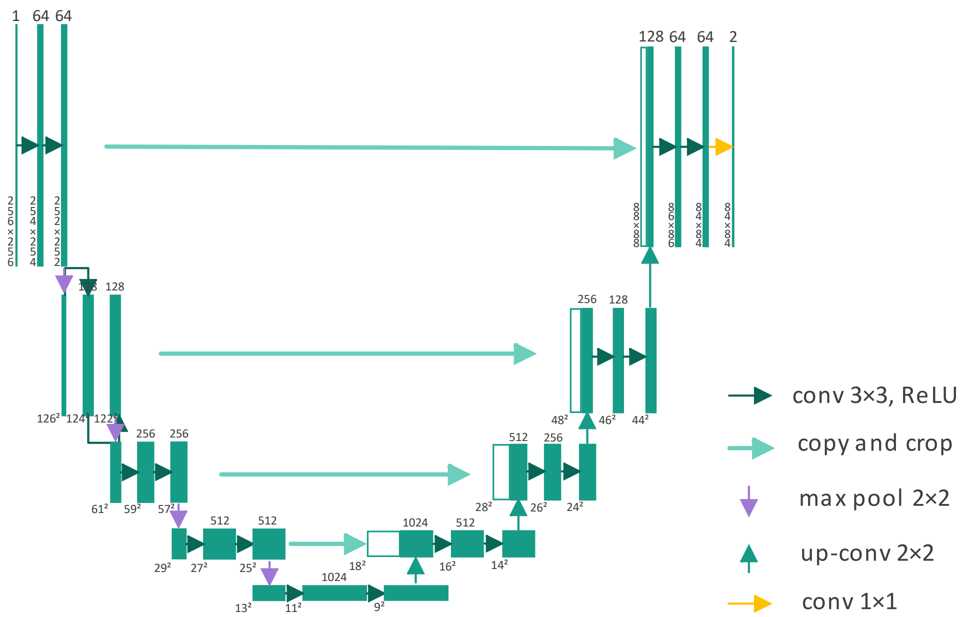


Figure 47. U-net Generation Network Structure.

U-net++ Network

The U-net model is based on an encoder-decoder structure, while the U-net++ is based on the U-net model, combined with DenseNet and deep supervision principles. Its main network structure is shown in Figure 48(144).

Specifically, the U-net++ model adds DenseNet modules at each stage of the encoder and decoder, which consist of densely connected convolutional layers to improve the performance and efficiency of the model. The U-net++ network with its nested structure and dense jump paths has a great advantage in extracting feature maps from multi-level convolutional paths. The biggest difference between U-net++ and U-net is the redesigned jump paths in U-net++. Take node $X^{0,4}$ as an example, in the U-net model structure, node $X^{0,4}$ simply constructs a jump connection with node $X^{0,0}$ a jump connection. In U-net++, node $X^{0,4}$ connects the outputs of the four convolution units $X^{0,0}$, $X^{0,1}$, $X^{0,2}$ and $X^{0,3}$, which are at the same layer. In addition, U-net++ introduces the principle of deep supervision to ensure the validity and stability of the model by adding supervised losses at each stage. This strategy allows the outputs of each stage to be fully utilized, thus improving the accuracy and robustness of the model. Such architecture of the U-net++ network has a great advantage in extracting feature maps from multi-level convolutional paths, making the semantic level of the feature maps within the encoder closer to the semantic level of the corresponding decoder part.

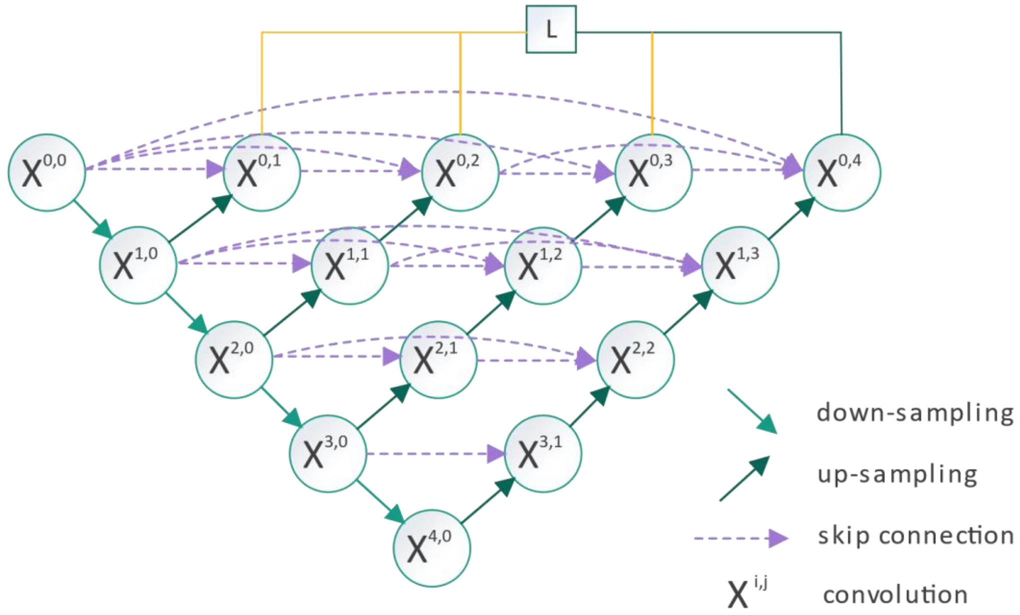


Figure 48. U-net++ Generation Network Structure.

Replacing the U-net structure with the U-net++ structure as the generator in the SD-GAN building façade generation training may bring the following improvements:

- Stronger Feature Representation

The U-net++ structure can better capture the multi-scale features and contextual information of the building façade by introducing more cross-layer connections and multi-scale feature fusion mechanisms compared to the traditional U-net structure. This can improve the feature representation capability of the generator, enabling it to learn the details and structural features of the building façade more accurately.

- Better Segmentation Results

The U-net++ structure is improved in terms of cross-layer connection and multi-scale feature fusion, which can better solve the information transfer and feature missing problems in the U-net structure. This helps the generator to better retain and recover details when generating building elevations, resulting in more accurate and clearer segmentation results.

- Better Consistency of Generation Results

The U-net++ structure can better maintain the resolution and contextual information of the feature map, which helps to improve the consistency of the generated results. Compared with the U-net structure, the U-net++ structure is easier to avoid the hesitation problem of the generator when generating building elevations, making the generation results more stable and consistent.

- Better Retention of Building Elevation Details

Since the U-net++ structure introduces more cross-layer connections and multi-scale feature fusion, the generator can better preserve and recover the details of the building facade. This includes windows, doors, walls, and other building components, resulting in more realistic and morphologically accurate building façades.

HRNet Network

HRNet (high-resolution net) was proposed in 2019 and has achieved good results in key point detection, pose estimation, and multi-person pose estimation. To verify the effectiveness of the HRNet network for building façade extraction, this study replaces the U-net generative network in the SD-GAN architecture with the HRNet generative network for experiments.

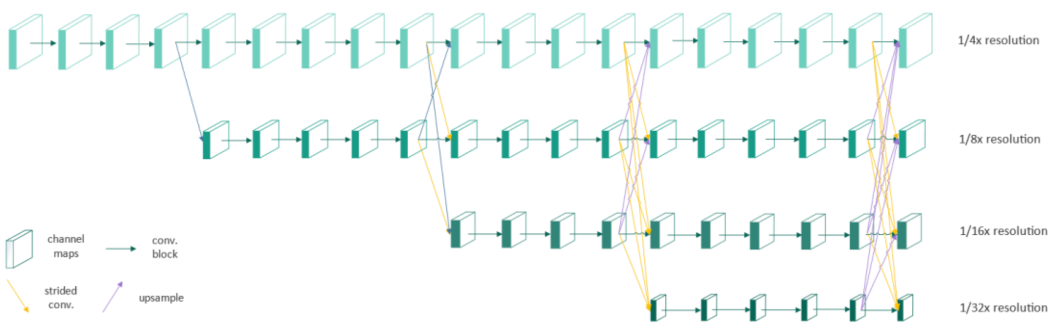


Figure 49. HRNet Generation Network Structure.

The HRNet neural network is a parallel structure that acts as an image feature skeleton extraction network (Figure 49). It uses 3 × 3 convolution for deeper down sampling while maintaining 4 times downsampling resolution to expand the perceptual field and extract deeper information about the image with a minimum resolution of 1/32 of the original image(145). Use the BasicBlock module in the forward propagation of the feature map of the same resolution and set the step size to 1. At the same time, the feature maps between different resolutions maintain information interaction, with multiple convolutions with a step size of 2 from high resolution to low resolution. As well, bilinear interpolation up sampling from low resolution to high resolution. Finally, information from different resolutions is received at each layer and stitched together in the channel dimension to complete the information fusion.

Each façade in the data set of this study has obvious block features, and its contextual semantic features are obvious. Special attention needs to be paid to the information on the boundaries when detecting the façade, and HRNet may make a great achievement in this regard. Therefore, replacing the U-net structure with HRNet as the generator in the SD-GAN building façade generation training may bring the following improvements:

- Stronger Multi-scale Feature Expression Capability

HRNet is a multi-resolution network structure that is able to maintain both high-resolution and multi-scale feature representation capabilities. Compared with the U-net structure, HRNet is able to better capture the details and structural features of the building façade, thus improving the feature representation capability of the generator.

- Better Modeling of Contextual Information

HRNet can effectively perceive the contextual information of the building façade through multi-level feature fusion and lateral connection. This enables the generator to have better context-awareness when generating building façade and can recover the details of façade structure and material more accurately.

- Better Image Segmentation Results

HRNet performs well on segmentation tasks with better edge preservation and detail recovery. Therefore, using HRNet as a generator structure can improve the segmentation effect of SD-GAN in building façade generation with more accurate and clearer generation results and sharper edges.

- Better Handling of Long-Distance Dependencies

HRNet is designed to handle long-distance dependencies and can better perceive long-distance structural connections in the building façade. This helps the generator to better maintain structural coherence and consistency when generating building facades, avoiding breaks or discontinuities in the generated results.

AttU-net Generation Network

In a normal convolutional network, the value of the target pixel is only calculated with reference to itself and the surrounding pixels. This means that convolution can only use local information to compute the target pixel, which may introduce some bias because the global information is not visible. In this study, the self-attention mechanism is introduced into the part of the down sampling of the U-net connected with the corresponding up sampling layer, and the hopping connection structure is preserved. This allows the network to fully mine global information and extract some details in the façade more accurately. The addition of the Attention gate to the U-net adds very little additional computation yet brings significant improvements in model sensitivity and accuracy, achieving a global reference for each pixel-level prediction(146).

As shown in Figure 50, the AttU-net network consists of an Encoder, a Decoder, and the Attention gate. A self-attentive module that passes through the encoding convolution module, extracts the bottom-level features, and then feeds a down sampling block to reduce the spatial size and obtain high-level features. The number of channels is doubled with each down-sampling block, and the end of the down-sampling is fed to the Attention module, which aggregates the global information and produces the output of the encoder.

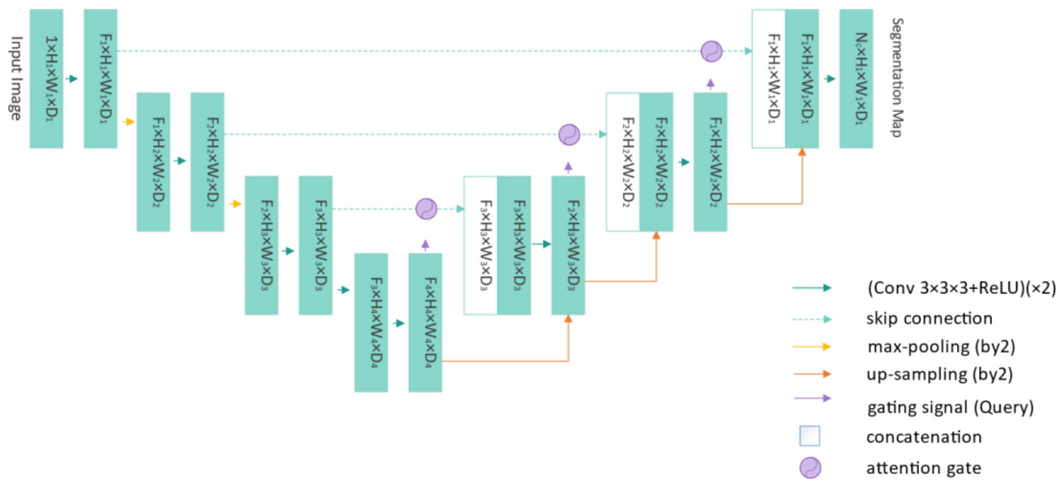


Figure 50. AttU-net Generation Network Structure.

Replacing the U-net structure with AttU-net as a generator in SD-GAN building façade generation training may lead to the following improvements:

- Better Attention Mechanism

AttU-net introduces an attention mechanism that enables the generator to pay more attention to important features and details by adaptively adjusting the weights at different positions in the feature map. Compared with the traditional U-net structure, AttU-net can capture key features and structural information in the building façade more accurately, thus improving the performance of the generator.

- Improved Detail Retention Capability

The attention mechanism in AttU-net helps the generator to better retain and recover the details of building facades. By adaptively adjusting the weights, AttU-net can accurately process the detail information of building façades, making the generated results clearer, more detailed, and maintaining more consistent morphological features with the real façade.

- Better Semantic Segmentation Effect

AttU-net combines the advantages of attention mechanism and U-net structure to improve the effect of semantic segmentation. The attention mechanism helps the generator to better understand and capture the semantic information of different regions when generating building facades, thus improving the semantic segmentation accuracy and precision of the generated results.

- Improving the Consistency of Generation Results

AttU-net's attention mechanism in the generation process helps to improve the consistency of the generated results. It helps the generator to better understand the structural and morphological features of the building façade and maintain the consistency of the generated results. This can avoid incoherence or breakage in the generated results and make the generated building facades more realistic and reasonable.

6.3.2. Training Epochs Re-Verification

In the SD-GAN model, the loss function of the model is optimized using the gradient descent algorithm. The whole iteration process is divided into two parts, the first part is the number of epochs with fixed learning rate, and the second part is the number of epochs with decaying learning rate. The number of epochs with fixed learning rate is to train a segment first according to a fixed step distance, which has the advantage of finding the region where the optimal solution is located more quickly. The epochs of decaying learning rate are then performed in the region where the optimal solution is located to better fit the lowest value of the loss function and reach the global optimal solution.

In order to reconfirm how many epochs are more effective to use after modifying the generator, and to clarify whether further optimization of the training process is needed, the epochs validation test was conducted again before the formal training. 6 experiments with different numbers of epochs were conducted for 100, 200, 300, 400, 500, and 800, respectively. In this section, take AttU-net generation network as an example, and the generation results for different number of epochs are shown in Figure 51.

The results in Figure 51 show that after 100 and 200 epochs, the color blocks of the generated pictures are more confusing and have more stray colors. After 300 epochs, the problem of stray colors in the color blocks is relatively improved, but the color blocks are still relatively chaotic. After 400 epochs, the accuracy of the images is better. After 500 and 800 epochs, because the number of training sets used is in the smaller category of deep learning, overfitting problems may arise when the amount of data is small, and the number of epochs is too large. Therefore, we can see that the training results after 500 epochs and 800 epochs are not as good as those after 400 epochs and consume longer time.

After a visual comparison of the images generated at different epochs, we can see that still the best results are generated at 400 epochs, both in terms of the accuracy of the images and the mixing problem between color blocks. Therefore, in the subsequent experiments, the SD-GAN is trained for 400 epochs to obtain the experiment results.

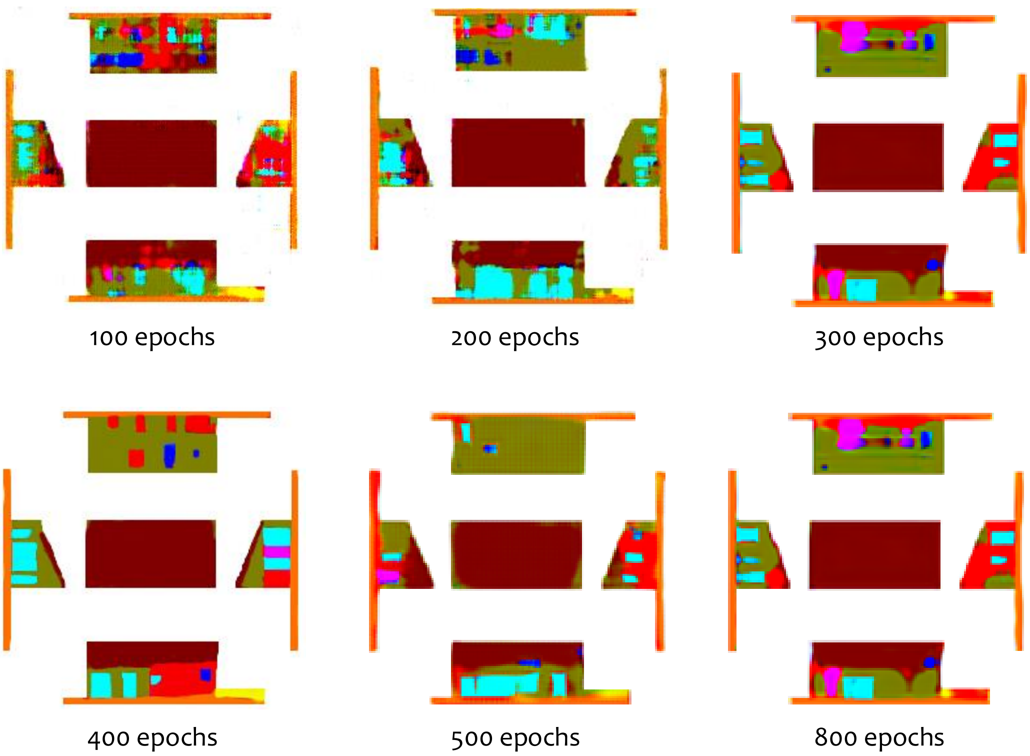


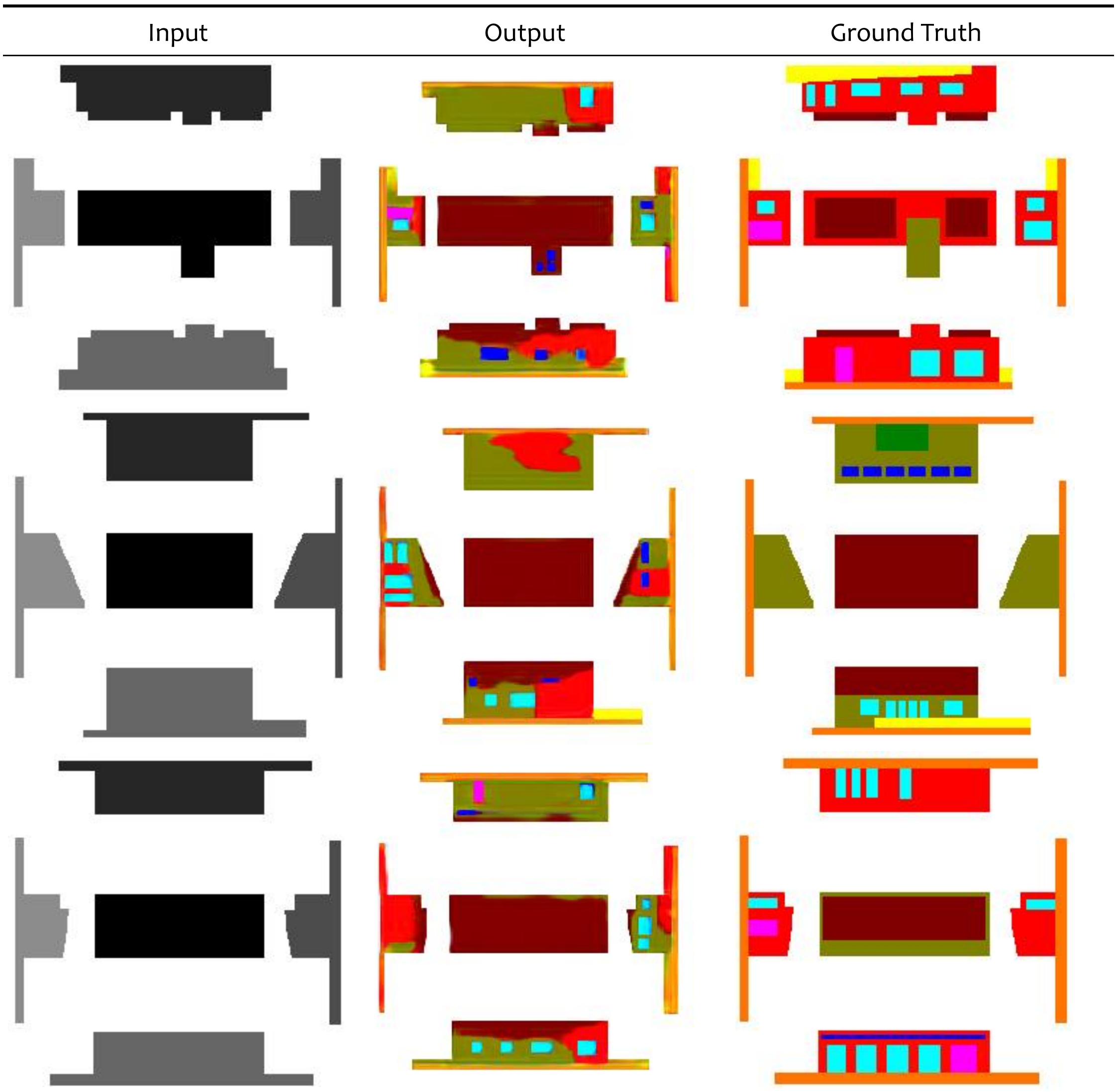
Figure 51. AttU-Net Generates Results with Different Number of Epochs

6.3.3. Replaced Training Results

Generating Results by Using the U-net++ Network

Table 19 shows the generated results using the U-net++ network, with the learning rate set at 0.0002 and the number of epochs at 400. The input to the model is the building façade boundary image, the trained Ground Truth is the building façade layout color block image, and the output is the output building façade layout color block image, taking a total of 3.5 h.

Table 19. Generating Results by Using The U-net++ Network.

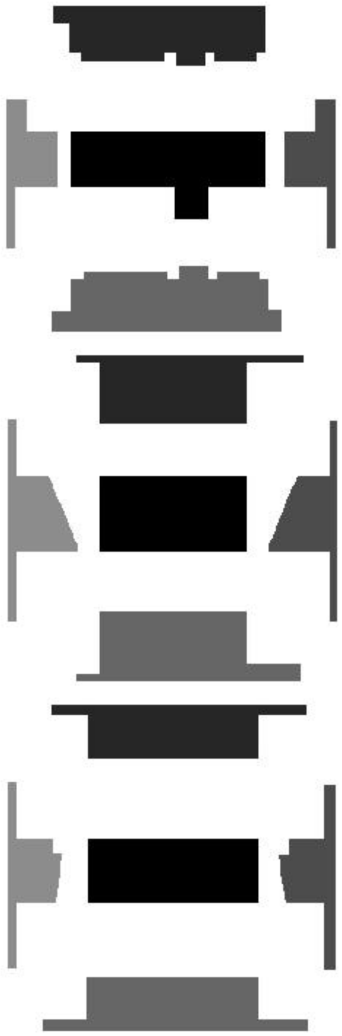
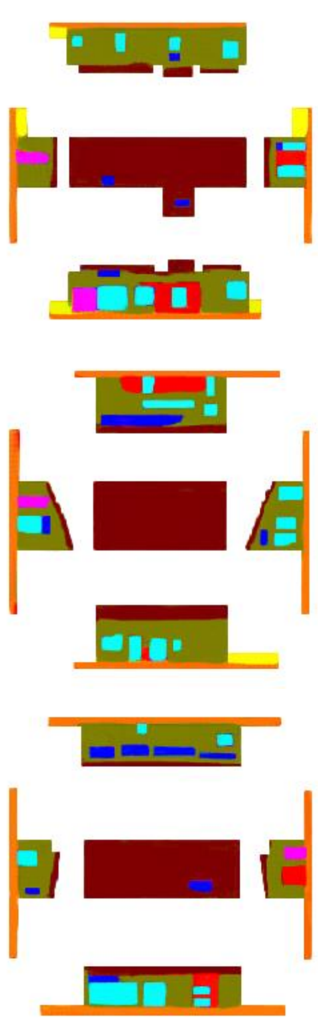
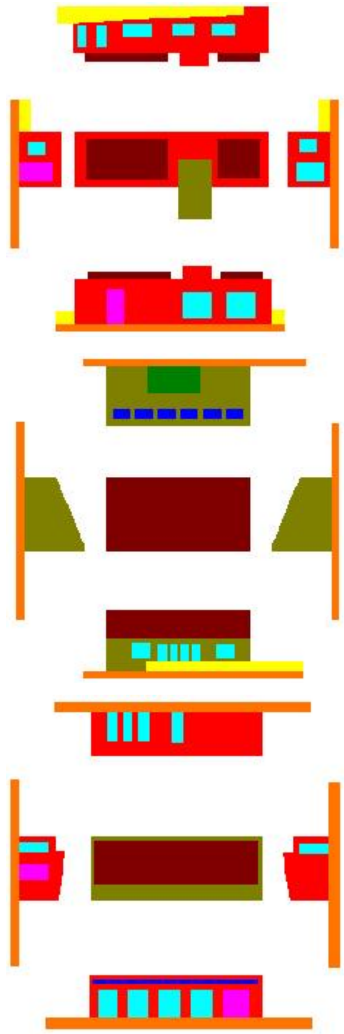


■ Photovoltaic Panels; ■ Plain Walls; ■ Greening; ■ Door; ■ Timber Walls;
■ Railings; ■ Windows; ■ High Windows; ■ Steps.

Generating Results by Using the HRNet Network

Table 20 shows the generated results using the HRNet network, with the same training parameter and environment with U-net, taking a total of 3 h.

Table 20. Generating Results by Using the HRNet Network.

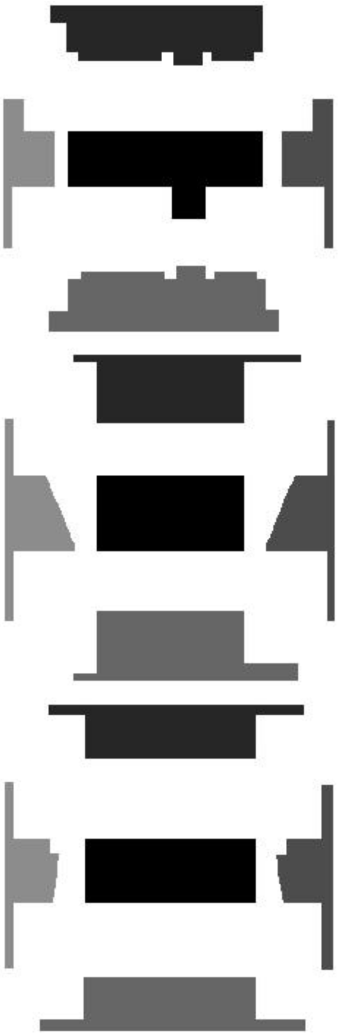
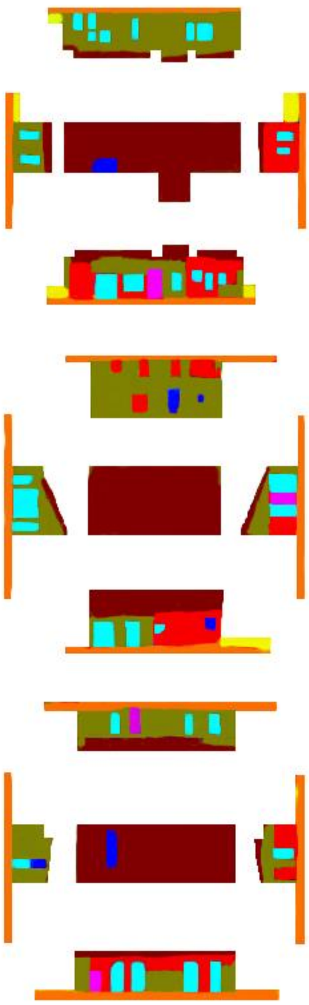
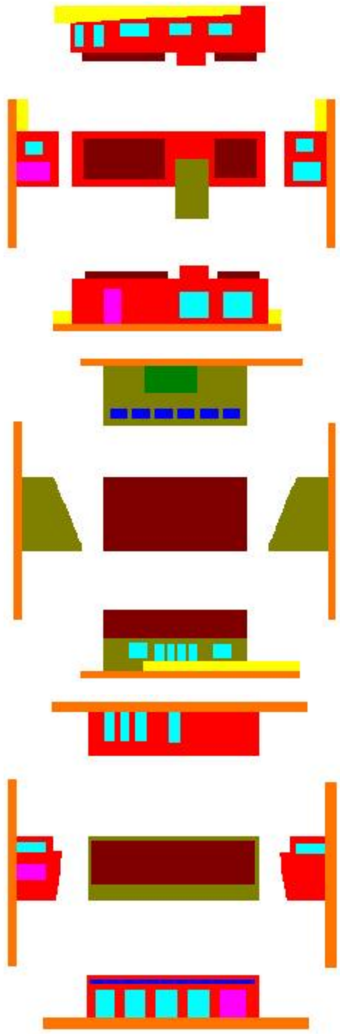
Input	Output	Ground Truth
		

■ Photovoltaic Panels; ■ Plain Walls; ■ Greening; ■ Door; ■ Timber Walls; ■ Railings; ■ Windows; ■ High Windows; ■ Steps.

Generating Results by Using the AttU-net Network

Table 21 shows the generated results using the AttU-net network, with the same training parameter and environment with U-net, taking a total of 4 h.

Table 21. Generating Results by Using the AttU-net network.

Input	Output	Ground Truth
		

■ Photovoltaic Panels; ■ Plain Walls; ■ Greening; ■ Door; ■ Timber Walls;
■ Railings; ■ Windows; ■ High Windows; ■ Steps.

6.4. Replaced Training Evaluation

6.4.1. Evaluation Method

The evaluation and discussion of the generation results are very important when conducting replacement experiments with structures of U-net++, HRNet and AttU-net. Proper evaluation can help compare the performance and effectiveness of different generator structures for building façade generation, including the quality, fidelity, detail retention capability and diversity of the generated results. This can help to select the most suitable generator structure for building façade generation. It can also help to understand and explain the effects of different generator structures on building façade generation. By evaluating the results of different generators, it is possible to gain insight into the strengths, weaknesses, and applicability scenarios of each structure. Finally, it will also be possible to reveal the potential for improvement and optimizing directions of the generator structures. The evaluation and discussion of the results can help identify problems and provide improvement strategies and ideas.

In this study, a combination of subjective and objective evaluation methods is introduced. The subjective evaluation method is able to capture subjective human opinions, aesthetic preferences, and user satisfaction. Objective evaluation methods, on the other hand, are able to quantify various aspects of the performance and quality of the generated results. The combined use of different evaluation methods can compensate for the limitations of subjective and objective evaluations and provide more comprehensive and accurate assessment results.

Subjective Evaluation

This phase developed a façade results questionnaire for experts based on the quality of the generated images, traditional architectural design requirements, as well as the subjective opinions of professional academics. The scoring table first subjectively evaluates the boundary condition and color block quality of the generated images, then evaluates whether the position, size, and proportion of the color blocks representing the façade components meet the requirements from the traditional architectural design perspective, as well as the architectural experts to evaluate the performance of the generated results and the façade design effect from the subjective aspect (Table 22).

Table 22. Questionnaire Scoring.

Questionnaire Item	Score （bad - good）
Generate Images with Clear Borders	0~5
Image Quality Without Aliasing	0~5
Generate Color Blocks in Reasonable Locations	0~5
Unity of the Whole and Parts	0~5
Harmony of Proportion and Scale	0~5
Energy Efficiency Performance	0~5
Design Performance	0~5

- Generate Images with Clear Borders

Experts can evaluate the clarity of the borders, i.e., the clarity and definition of the boundary lines, of the building façade in the generated results. Clear borders help to accurately identify and separate the different components of the building, making the building façade clearer and more recognizable.

- Image Quality without Aliasing

Experts can evaluate whether the image quality in the generated results is undesirable such as blurring, noise or artifacts. A non-aliased image should have good detail retention, color accuracy and texture coherence.

- Generate Color Blocks in Reasonable Locations

Experts can evaluate whether the position of color blocks in the generated results is reasonable. The color blocks should be generated in accordance with the design pattern and style of the building façade and be connected and coordinated with the surrounding components.

- Unity of the Whole and Parts

The expert can evaluate the unity between the whole and the parts of the building façade in the generated results. The parts of the façade should form a coordinated and harmonious whole, maintaining consistency in style, proportion and design elements.

- Harmony of Proportion and Scale

Experts can evaluate the harmony of the proportions and scale of the building façade in the generated results. The various parts of the building, such as windows, doors, and walls, should maintain a reasonable relationship of proportion and scale within the overall façade to ensure visual balance and aesthetics.

- Energy Efficiency Performance

Experts can evaluate the energy efficiency performance of the building façade in the generated results based on subjective design intuition. This includes an assessment of the façade's insulation performance, lighting effectiveness, and solar energy use to ensure that the generated results meet general energy efficiency and sustainability design requirements.

- Design Performance

Experts can evaluate the design performance of the building façade in the generated results, such as innovation, aesthetic value, and compliance with human occupancy requirements. This includes an assessment of the innovative and functional aspects of the façade design.

The subjective evaluation by experts allows for input and feedback with specialized knowledge and aesthetic insight, thus providing a comprehensive, accurate and integrated assessment of all aspects of the generated results and helping to improve and optimize the performance and quality of the generated model of the building façade.

Objective Evaluation

In addition to relying on the above subjective façade evaluation questionnaire for the evaluation of low-rise residential façade generation results, this phase also introduces objective evaluation criteria.

In general, methods for evaluating image similarity include structural similarity metric (SSIM), mean square error (MSE), and regularized root mean square error (NRMSE). By comparison, SSIM is more suitable for the evaluation of building façade generation tasks for the following main reasons:

- Considering Human Eye Perception Features

SSIM is a structural similarity indicator that considers the features of human eye perception. Compared with MSE and NRMSE, which focus only on pixel-level differences, SSIM can better measure the similarity of images in terms of structure, texture, and details, and is more in line with the human eye's perception of image quality.

- Insensitivity to Contrast and Luminance

MSE and NRMSE are more sensitive to changes in luminance and contrast. While in building façade generation, variations in luminance and contrast may be reasonable because building façades may have different lighting conditions and material representations. SSIM can offset the effects of these factors on similarity evaluation to some extent by introducing three components of luminance, contrast, and structure.

- Better Structure Perception Performance

The goal of building façade generation is to generate images that match the structure and materials of the building façade. SSIM can better capture and measure the structure characteristics of the building façade by considering the structural information of the images when calculating similarity. In contrast, MSE and NRMSE calculate only pixel-level errors and cannot provide information about structural and material aspects.

Therefore, although MSE and NRMSE are common image evaluation metrics, they are more applicable to pixel-level comparisons than to the evaluation of structural and material features. In the task of building façade generation, SSIM is more suitable for objective evaluation as a structural similarity indicator that better reflects human eye perception and importance to structural features(147).

6.4.2. Subjective Evaluation

In this phase, questionnaires were distributed to architects and master's students with architecture education background (complete architecture training at both undergraduate and master's level) through a targeted WeChat group. The questionnaire was sent out in January 2023 and lasted for one week, 36 questionnaires were returned, the distribution of the feedback is shown in Figure 52, the scores of the feedback are shown in Figure 53, and the combined mean values are shown in Table 23.

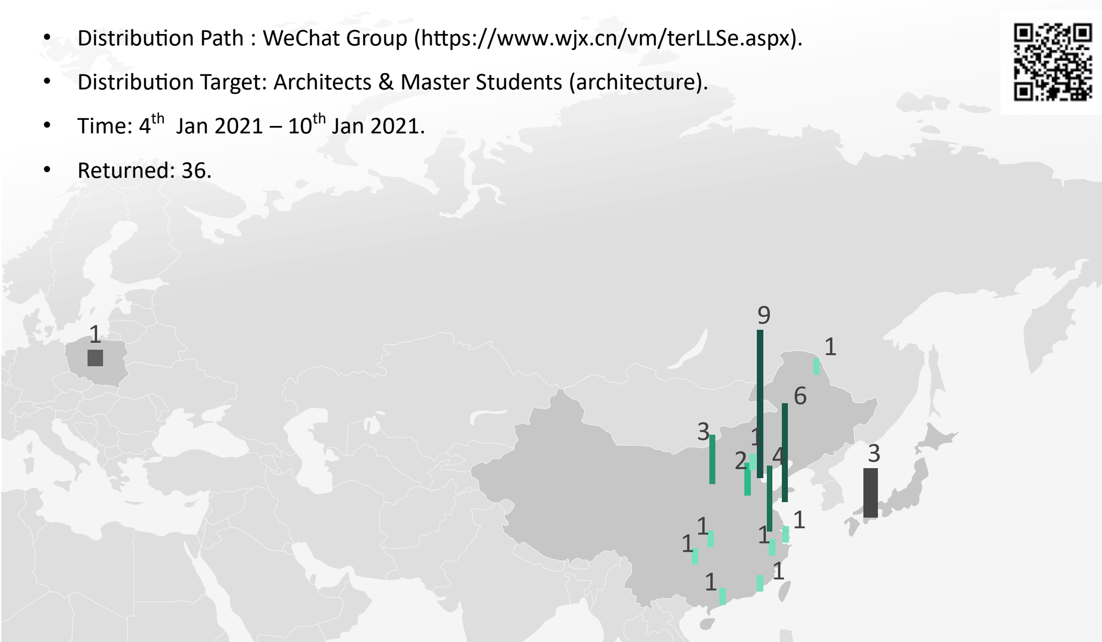


Figure 52. Distribution of Returned Questionnaires.

	Q1-U-net	Q2-U-net	Q3-U-net	Q4-U-net	Q5-U-net	Q6-U-net	Q7-U-net
Q3-MEDIAN	1.75	2	2	2	1.75	2	1.5
MEDIAN-Q1	1	1	0	0.75	1	0.75	1.5
Q1	2	1	2	1.25	2	1.25	1
MEDIAN	3	2	2	2	3	2	2.5
STDEV	1.47	1.46	1.38	1.48	1.47	1.39	1.48

	Q1-U-net++	Q2-U-net++	Q3-U-net++	Q4-U-net++	Q5-U-net++	Q6-U-net++	Q7-U-net++
Q3-MEDIAN	1	1	1	1	1	1	1
MEDIAN-Q1	0	1	1	0.75	1	1	1
Q1	3	2	2	2.25	2	2	2
MEDIAN	3	3	3	3	3	3	3
STDEV	1.14	1.18	1.27	1.09	1.23	1.14	1.12

	Q1-HRNet	Q2-HRNet	Q3-HRNet	Q4-HRNet	Q5-HRNet	Q6-HRNet	Q7-HRNet	Q1-AttU-net	Q2-AttU-net	Q3-AttU-net	Q4-AttU-net	Q5-AttU-net	Q6-AttU-net	Q7-AttU-net
Q3-MEDIAN	1	1	1	1	1	1.5	1	1	1	0.75	1	1	1	1
MEDIAN-Q1	0	1	1	1	0.75	0.5	1	0	0	1	0	0	0	0
Q1	4	3	3	3	3.25	3	3	4	4	3	4	4	4	4
MEDIAN	4	4	4	4	4	3.5	4	4	4	4	4	4	4	4
STDEV	0.91	1.27	1.16	1.06	0.85	1.02	1.09	1.1	0.96	0.92	0.69	0.83	0.94	0.95

Figure 53. Chart of the Values of Each Questionnaire Item.

Table 23. Mean Results of The Questionnaire.

Questionnaire Item	U-net	U-net++	HRNet	AttU-net
Generate Images with Clear Borders	3	3.4	4	4.1
Image Quality Without Aliasing	2.5	3.1	3.7	4
Generate Color Blocks in Reasonable Locations	2.7	3.2	3.8	3.9
Unity of the Whole and Parts	2..7	3.2	3.8	4.2
Harmony of Proportion and Scale	3	3.3	4.1	4.2
Energy Efficiency Performance	2.6	3.1	3.7	4.1
Design Performance	2.7	3.1	3.8	4.1
Comprehensive Mean	2.7	3.2	3.8	4.1

The results show that HRNet and AttU-net scored higher in generating image boundaries. the U-net results suffer from blurred outer wall boundaries, and U-net++ improved slightly, but still falls slightly short. In terms of aliasing in the functional color block mapping, AttU-net performs better, while U-net scores lower. This indicates that the HRNet and AttU-net structures have stronger feature representation capability and multi-scale feature fusion mechanism, which can better capture image boundary and edge information and thus generate images with clear boundaries. In contrast, the U-net structure may have certain defects in the retention of boundary details, leading to the problem of blurred boundaries.

From the perspective of traditional architectural design, AttU-net and HRNet perform better in terms of the position of functional color block generation, unification of the whole and parts, and coordination of proportion and scale. It is evident that AttU-net can generate more accurate and reasonable functional color block mapping by better focusing on the generated position and features of functional color blocks through the introduction of attention mechanism. HRNet and AttU-net structures can better maintain the consistency and coordination between the overall façade and part components, as well as the harmony of proportion and scale through multi-scale feature fusion and cross-layer connection mechanism. This makes the generated results more in line with the requirements and aesthetic views of traditional architectural design. In contrast, U-net and U-net++ scored lower.

The architecture experts believe that AttU-net's generated results may be superior in terms of performance. On the other hand, U-net may not perform as well. As for the façade design results, the experts' scoring results show that both the AttU-net generator and the HRNet generator have acceptable façade design results, which means that AttU-net and HRNet are able to generate results that meet façade design requirements and standards.

In terms of active energy saving measures, unfortunately none of the generators were able to generate green roofs and vertical greening. This may be due to the small number of samples of green roofs and vertical greening in the training set. However, the AttU-net generator and the HRNet generator performed well in generating PV panels. The generated PV panels have regular shapes and reasonable positions, which meet the requirements of building energy efficiency well.

Therefore, HRNet and AttU-net perform better in the building façade generation task compared to U-net and U-net++ and are better able to generate building façades with clear boundaries, reasonable functional color blocks, unified whole and parts, and harmonious proportions and scales.

6.4.3. Objective Evaluation

The SSIM was used for the objective evaluation. However, the calculation of SSIM values by comparing the generated results with which data still needs to be explored. In this phase, the calculation of SSIM values from the generated results to the ground truth (color block labeled maps) is proposed.

The experiments were conducted by random sampling and 3 samples were randomly selected from 98 data sets as the test set. After the training was completed, the three test sets were input into the test program for testing, and the generated results were compared with the input solution to calculate their SSIM values. The output SSIM values are shown in Table 24, and their average results were calculated for the SSIM values of each generated result.

The value of SSIM ranges from 0 to 1. When SSIM = 1, it means that the two images are identical. When the value of SSIM is smaller, it means that the difference between the generated image and the target image is greater. The SSIM values for the three samples in the four sets of networks are represented in Figure 54.

Table 24. SSIM Values and Mean Value Calculation.

Generators Category	U-net	U-net++	HRNet	AttU-net
Sample 1 SSIM values	0.65713	0.71054	0.82845	0.86215
Sample 2 SSIM values	0.59921	0.68433	0.76534	0.81084
Sample 3 SSIM values	0.62185	0.69831	0.77015	0.83233
SSIM average	0.626	0.697	0.788	0.835

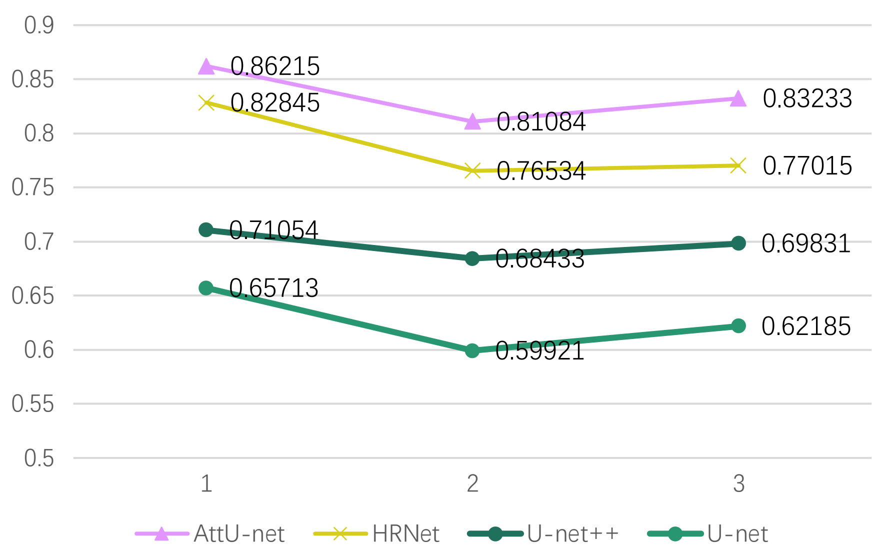


Figure 54. SSIM Values Comparison.

The SSIM test results show that AttU-net has the highest score above 0.8, which is consistent with the subjective evaluation of image sharpness and color purity. This result indicates that AttU-net outperforms HRNet in terms of image sharpness and color purity. In contrast, HRNet scores slightly lower than AttU-net, but still achieves 94% similarity, indicating that it still performs quite well in generating image quality.

From a practical point of view, HRNet may have more advantages in terms of training speed and solution generation. Since HRNet has a simpler network structure compared to AttU-net, its training time may be shorter, and its generation speed may be faster. Therefore, if fast training and solution generation are needed in a specific situation, HRNet may be a viable option.

6.4.4. Benchmarking Calculation

In order to clarify the above observations, in this stage, the subjective and objective scores of each of the 3 alternative networks were further processed in accordance with Equation (6-1 using U-net as the benchmark score to calculate the final efficiency score of each generative network. This operation considers the multiplicative scores of each generating network in terms of subjective evaluation mean, subjective evaluation stability, SSIM and training time.

$$E_x = \frac{\left(\overline{M_x}/\overline{M_U}\right) \times \left(\overline{S_x}/\overline{S_U}\right)}{T_x/T_U} = \frac{\sum_{i=1}^{7} Q_{x_i} \times \sum_{i=1}^{3} S_{x_i} \times t_U}{\sum_{i=1}^{7} Q_{U_i} \times \sum_{i=1}^{3} S_{U_i} \times t_x} \tag{6-1}$$

Where E_x is the energy efficiency branch of x-network, M_x is the subjective evaluation mean value of x, M_U is the U-net subjective evaluation mean value, S_x is the STDEV value of x, S_U is the STDEV value of U-net, T_x is the training time of x, T_U is the training time of U-net, and Q_{x_i} is the score obtained for the i question of x.

The calculated results are shown in Table 25, and Figure 55 shows the score distribution.

Table 25. Benchmarking Calculation Results

	U-net	U-net++	HRNet	AttU-net
Mean Times	1	1.16	1.39	1.47
SSIM Times	1	1.11	1.26	1.33
Timely	1	0.71	0.83	0.63
Efficient	1	0.92	1.45	1.22

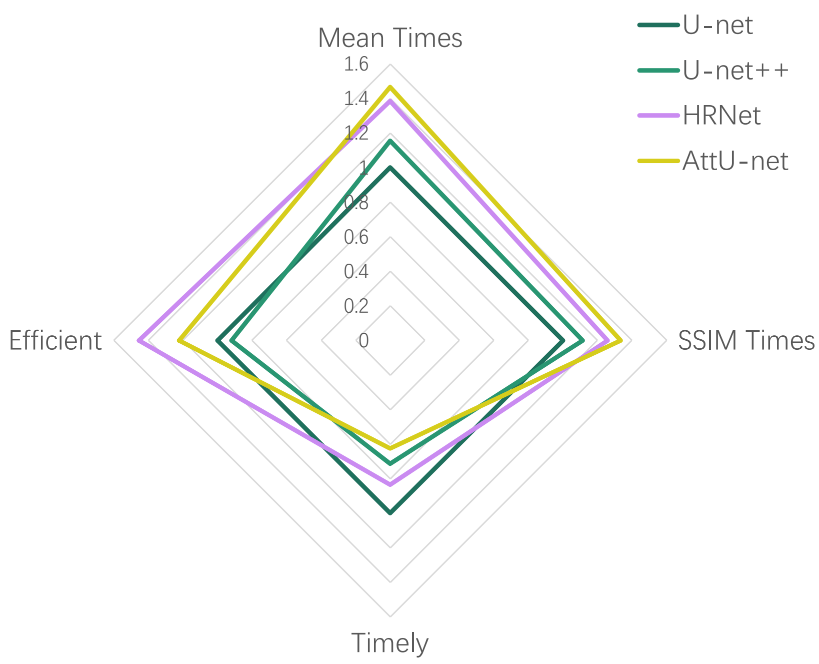


Figure 55. Chart of Benchmarking Calculation Results.

The graphs allow relatively refined conclusion of this generator replacement experiment as follows:

- HRNet and AttU-net excelled in subjective and objective evaluations.

HRNet and AttU-net have a more complex and powerful network structure, and they are able to better preserve image details, improve image quality and realism compared to U-net and U-net++. This results in HRNet and AttU-net performing better in subjective and objective evaluations, generating results that are more in line with human eye perception and building façade requirements.

- HRNet and AttU-net have outstanding performance on the efficiency ratio.

The training time of HRNet is the shortest among the 3 alternative networks. Due to the shortened training time, HRNet is able to complete the training and generate high-quality building façades in a shorter period of time. This results in HRNet outperforming AttU-net and U-net++ in terms of efficiency ratio. The shorter training time also means higher training efficiency and faster solution generation, making HRNet a better choice for fast training and solution generation.

- Relatively poor performance of U-net and U-net++.

Compared with HRNet and AttU-net, the network structure of U-net and U-net++ is still relatively simple. This may be the main reason for the relatively poor performance in terms of image detail retention, image quality and fidelity. In addition, the longer training time of U-net++ may require more computational resources and time to achieve comparable performance to HRNet and AttU-net.

Therefore, in the subsequent empirical study, HRNet and AttU-net will be used for the generation of integrated architecture solutions, respectively, to present the relatively complete process and results of collaborative human-AI architectural design proceeding.

6.5. Summary

The purpose of this chapter is to explore the method to continue to improve the generative power of SD-GAN by replacing the generator networks. In the experiments, the U-net generation network in SD-GAN was replaced with U-net++, HRNet and AttU-net, respectively, by continuing to use the entries of SD competition as samples. After that, the candidate networks were evaluated for the generation results by a comprehensive subjective and objective evaluation.

1. The subjective evaluation showed that the AttU-net generator and the HRNet generator had acceptable façade design results in terms of façade design results.

2. The generated results show a certain degree of energy efficiency, especially the reasonable shape and position of the photovoltaic panel.

3. The average structural similarity between the results of the AttU-net generation network and the target color block diagram was greater than 0.8. Indicates that the replacement of the U-net generation network of SD-GAN with the AttU-net generation network in this chapter can generate a more reasonable comprehensive building façade layout.

4. Compared with traditional parametric design, the method used in this chapter is able to use deep learning to discover the patterns in the façade layout and generate façade layouts efficiently.

5. AttU-net has the best generation performance. Considering that approximately 25% of training time can be saved, HRNet is another acceptable choice in scenarios where there is a need for fast training and generation. The subjective scores of its generated results are 7% lower than AttU-net and 6% lower in SSIM value.

In general, the generator replacement experiments conducted in this chapter can improve the generation capability of SD-GAN to a large extent, and the evaluation results are relatively stable in all aspects. However, it still needs to be noted that no matter which generator is used, there are still some limitations in performance, and human intervention is still needed and necessary for modification. In addition, the overall generation of building plan and façade, as well as the integration of active and passive strategies, still need to be studied in future research to build a more comprehensive model of energy-efficient buildings.

Chapter 7. Empirical Study

7.1. Introduction

After the first two strategies proposed by Chapter 3 above, this chapter will implement the 3rd strategy: empirical study. This phase consists of 4 steps:

First, based on the reference cases (Case A, Case B, Case C), building plan solutions (Solution P-A, Solution P-B, Solution P-C), HRNet-generated façade solutions (Solution F_H-A, Solution F_H-B, Solution F_H-C), the AttU-net generated façade solutions (Solution F_A-A, Solution F_A-B, Solution F_A-C) will be generated respectively.

Secondly, the coupling degree of the building plan and façade generated by SD-GAN is compared by comprehensive evaluation and analysis of the above generated results to examine whether they need to be modified artificially. The subjective evaluation mainly observes the coupling degree of plan function and façade form and examines the actual effect of the design solutions. The objective evaluation, on the other hand, is measured according to the relevant design codes such as GB 50033-2013 and JGJ 26-2018, and the design solutions are evaluated from the code perspective.

Thirdly, in order to ensure the comparability of the simulation results in the later stage, the façade generation solutions will be appropriately corrected based on the plan generation solutions according to the principle of minimum correction. Finally, the modified solutions based on HRNet (Solution M_H-A, Solution M_H-B, Solution M_H-C) and the modified solutions based on AttU-net (Solution M_A-A, Solution M_A-B, Solution M_A-C) will be collated.

Fourth, in order to verify whether the generated models have certain energy saving effects, energy consumption simulations are performed for the reference cases (3) and the modified solutions (6) by DesignBuilder. Again, to focus on the influence of basic design elements (e.g., building form, doors, windows, etc.) on the simulation results, parameters such as environment, materials, and construction methods are fixed in the simulations, and the performance of each solution is elaborated in terms of total annual energy consumption, annual cooling energy consumption, and annual heating energy consumption. These simulation results will be carefully dissected and discussed to reveal the reasons for their generation and to verify the possibility and validity of the building design solutions obtained through human-AI collaboration.

It is hoped that the series of empirical studies of " Generation-Evaluation-Adjustment-Simulation" will provide a method and process reference for future human-AI collaborative architectural design and provide a valuable reference for future research work.

7.2. Reference Cases

The base area of Case A is roughly 160 m^2 while the indoor area is about 95 m^2 in the form of a single-story monolith. It was renovated in 2009 and is fully functional. The width of the building is about 12.8 m, and the depth is about 7.8 m. As shown in Figure 56, the living room is in the middle of the house. The bedrooms are on the south side separated from the living room. The kitchen and bathroom are located at two corners of the north side.

Case B building form is single-story L-shaped, with an area of about 110 m^2. As shown in Figure 57, the living room is in the middle with 3 bedrooms on the east and west sides. The kitchen and storage room have independent entrances to the courtyard.

The building area of Case C is about 90 m^2 with a single-story U shape. As shown in Figure 58, the living room is also in the middle, but two bedrooms are located on the east side only. The kitchen, storage room, and bathroom are arranged on the west side, and the kitchen has a separate opening to the courtyard.

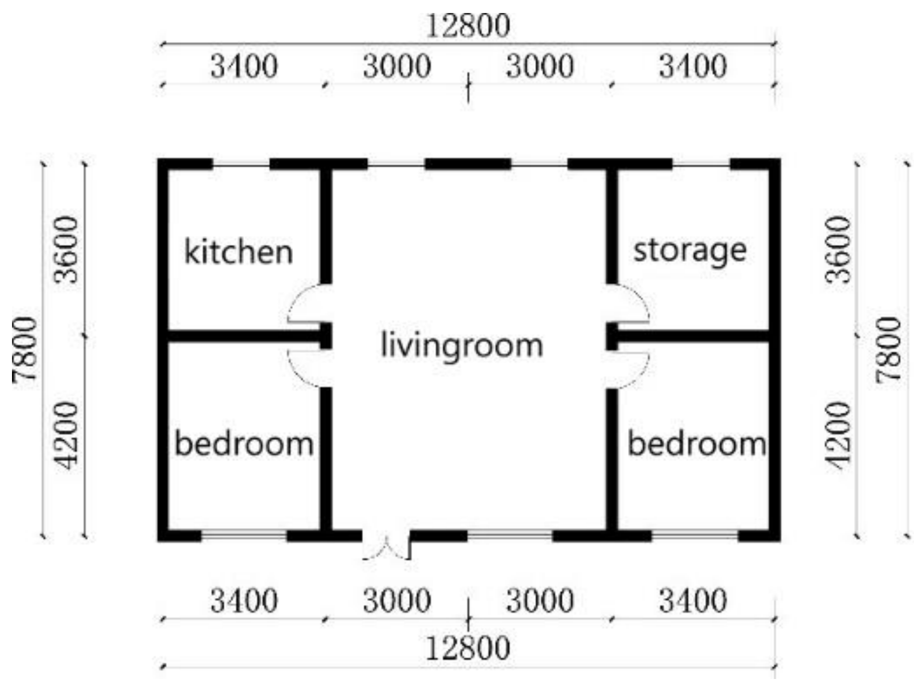


Figure 56. Case A BFP.

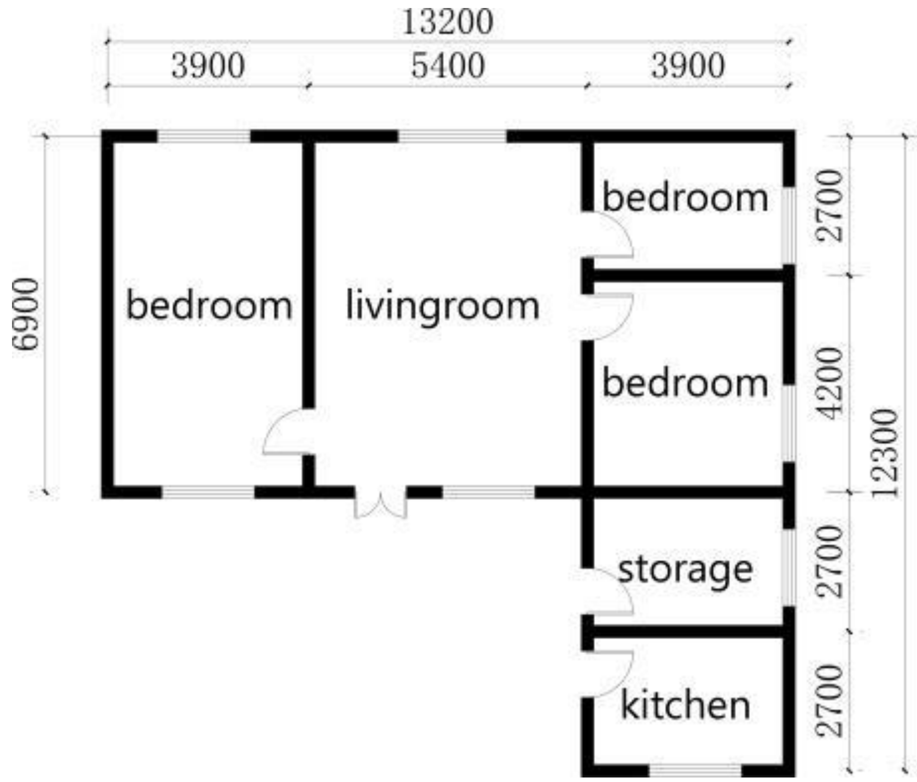


Figure 57. Case B BFP.

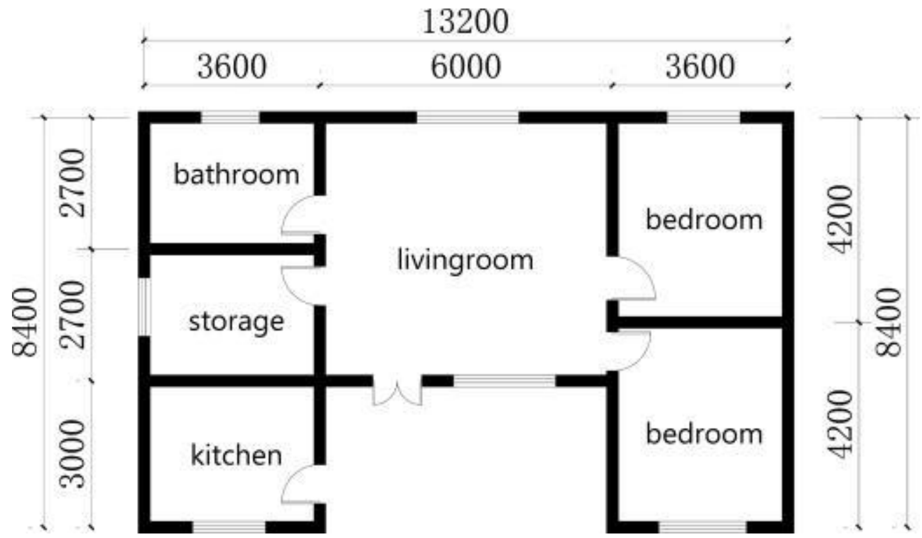


Figure 58. Case C BFP.

The 3 cases selected for this phase of the experiment have many strengths in the empirical study:

Representativeness and Building Type Consistency

They are all typical one-story residential building types in rural northern China. The 3 cases have different forms, rectangular, L-shaped and U-shaped respectively. This choice allows for a better representation of the typical residential building types in the region and is consistent with the building types of the SD competition entries. This can make it more practical to compare and evaluate the architectural designs generated by SD-GAN.

Controllability of the Experiment

The structures in all 3 cases are of brick and concrete construction with high heat transfer coefficients in the exterior envelope. This makes it easier to observe the energy efficiency performance of the generated solutions with other parameter settings fixed. By conducting experiments under these consistent conditions, the improvement in energy efficiency of the SD-GAN-generated building designs can be more accurately evaluated.

Easy to Simplify Energy Efficiency Evaluation

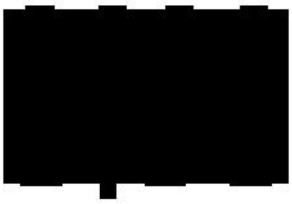
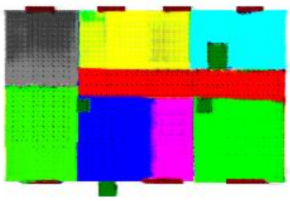
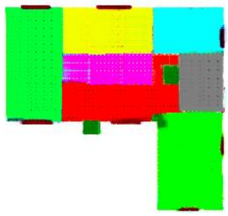
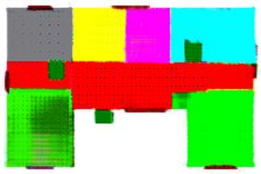
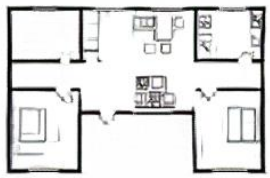
Compared to large buildings or complex building systems, these 3 small-scale residences are easier to handle in terms of energy efficiency assessment. Due to their relatively simple structures and functions, the effects of factors such as changing the layout and the size of window and door positions on energy efficiency performance are more intuitively visible. Therefore, selecting these cases as reference objects makes it easier to observe the effect of SD-GAN-generated building designs in terms of energy efficiency improvements.

7.3. Comprehensive Generation

7.3.1. Plan Generation

After thorough training by Chapter 4 to Chapter 6 above, SD-GAN was fed with the 3 cases' BEPs to generate the FSLs and BFPs, which shown in Table 26. The results show that each functional segmentation, boundary, and plan is sufficiently obvious for further simulation, while the layout generated is fairly reasonable.

Table 26. SD-GAN Plan Generation Results.

Item	Case A	Case B	Case C
BEP			
Generated FSL			
Generated BFP			
	(Solution P-A)	(Solution P-B)	(Solution P-C)

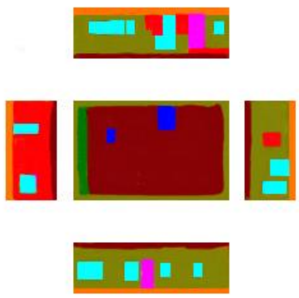
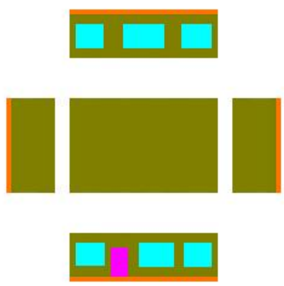
7.3.2. Façade Generation

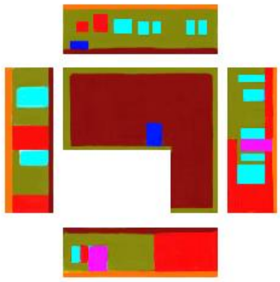
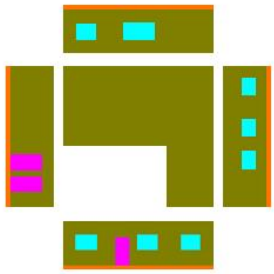
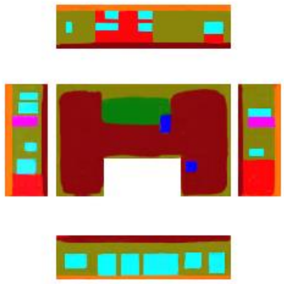
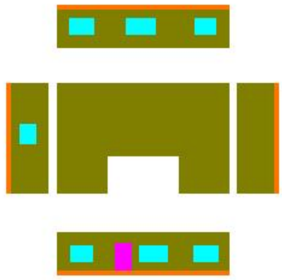
As mentioned in Chapter 6 above, the 4 generative networks employed in this research were subjectively and objectively evaluated. The AttU-net and HRNet neural network have a higher overall score. Therefore, these 2 networks are used for the generation based on the 3 cases in this study. HRNet-is used to generate façade solutions: Solution F_H-A, Solution F_H-B, and Solution F_H-C, respectively. While the AttU-net is used to generate façade solutions: Solution F_A-A, Solution F_A-B, and Solution F_A-C, respectively.

By observing, compared with the original cases, HRNet generates a large number of photovoltaic panels on the roof and some green roofs (Table 27), which can provide photovoltaic power generation for the building. In the design of the façade, HRNet generates more windows and more design elements compared with the real solution, but in general, the windows are generated in a rather fragmented manner and look rather disorganized.

HRNet shows good energy efficiency and sustainability awareness in the generation of PV panels and green roofs. However, there may be some shortcomings in window generation that need to be improved through subsequent manual adjustments and optimization. This suggests that the generation model can provide useful ideas and design elements, but still requires human intervention and designer expertise for further refinement and refinement.

Table 27. Façade Generation Results for SD-GAN Using HRNet as Generator.

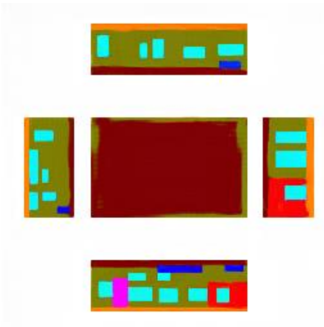
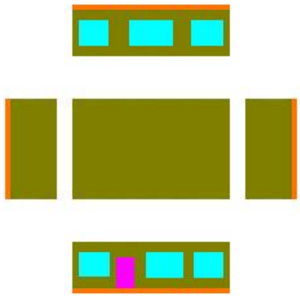
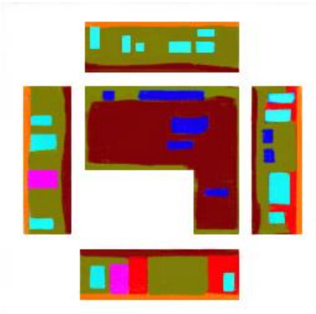
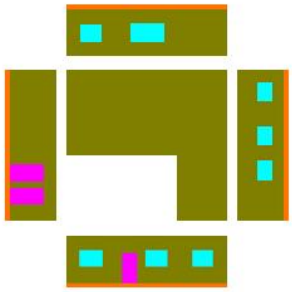
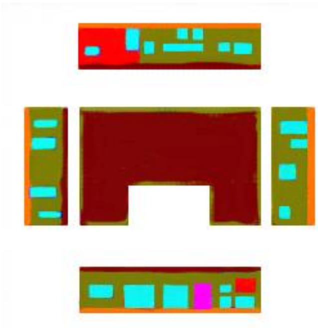
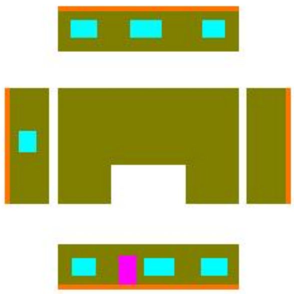
Item	Input	Output	Ground Truth
Case A		 (Solution F_H-A)	

Item	Input	Output	Ground Truth
Case B			
		(Solution F_H-B)	
Case C			
		(Solution F_H-C)	

AttU-net's generation solution also generates a large number of photovoltaic panels on the roof compared to the real solution (Table 28). And in Solution B, it can be observed that a large number of skylights are generated on the roof, which can provide more lighting to the rooms, and the photovoltaic panels can also provide some power generation for the building, reducing the energy consumption of the building. In the design of windows and doors, AttU-net basically generates entry doors on the south elevation. The design of windows is slightly fragmented compared to the original proposal, although it adds some design sense.

In contrast to HRNet, AttU-net also focuses on the design aspects of energy efficiency and sustainability. In Solution B, the generation of skylights may be a design decision by AttU-net in considering comfort and indoor environmental quality. In the prevailing generation scenario, AttU-net shows a clear constraint and preference for the generation of functional doors on the south elevation. However, there may be some fragmented distribution in the generation of windows, which may be its attempt to provide useful ideas and design elements, but still requires the expertise and intervention of the designer for further refinement.

Table 28. Façade Generation Results for SD-GAN Using AttU-net as Generator.

Item	Input	Output	Ground Truth
Case A			
		(Solution F_A-A)	
Case B			
		(Solution F_A-B)	
Case C			
		(Solution F_A-C)	

7.4. Coupling Analysis

After the plan and façade generation of the solution is carried out, the coupling degree between them should be analyzed. The coupling degree of the plans and façades is actually the compatibility of the functional rooms of the plan with the building elements such as doors and windows of the façade. The data of the plans is generated with the U-net generation network, while the façades are generated with two networks, HRNet and AttU-net. Therefore, the generation results of these two networks need to be coordinated with the results of the plans.

7.4.1. Subjective Analysis

Coupling Degree Subjective Analysis of HRNet Generated Façades and Plans

- Case A

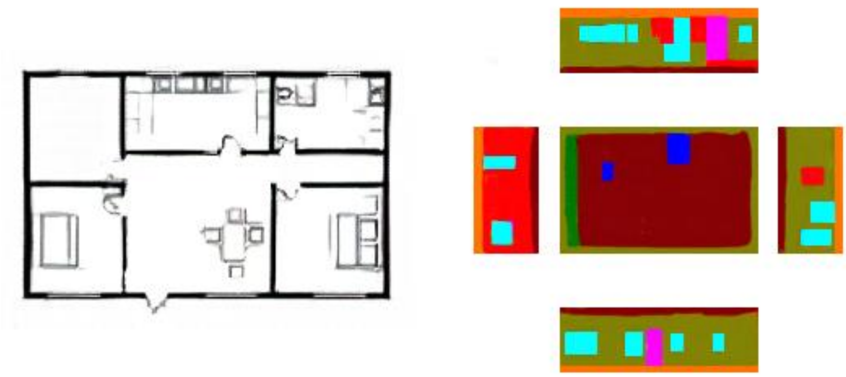


Figure 59. Solution P-A (left) and Solution F_H-A (right).

In Case A, the rooms corresponding to the south direction of the plan are the secondary bedroom, the living room, the dining room and the master bedroom from west to east. In the façade generation solution, the door of the south elevation is generated in the living room position, and the corresponding windows of the master bedroom and the secondary bedroom are also generated, indicating a good coupling situation.

The corresponding rooms in the north direction of the plan are equipment room, kitchen and bathroom from west to east in order. In the façade generation solution, the north elevation has a secondary entrance in the bathroom and a floor-to-ceiling window in the kitchen. These are subjectively mismatched. Therefore, we need to adjust the Solution F_H-A here. The door corresponding to the bathroom location is eliminated and the size of the kitchen window should be adjusted.

The windows generated in the east and west elevations match better with the rooms of the plan and do not need to be adjusted. The roof photovoltaic and high window generation are reasonably located and also do not need to be adjusted.

- Case B

Figure 60. Solution P-B (left) and Solution F_H-B (right).

In Case B, the location of the entrance door on the south elevation is unreasonable, as it is located in the master bedroom on the plan and needs to be adjusted to the living room. The windows on the south elevation are relatively small, and the lighting is not suitable for the living room and the two bedrooms, hence the need to increase the windows on the south elevation in Solution F_H-B.

The east elevation has a secondary entrance at the equipment room location on the plan, which allows direct access to the equipment room from outside, which is more convenient and reasonable.

The windows generated on the rest of the elevations match the plan room well and do not require adjustment. The photovoltaic and high windows generated on the roof are reasonably located and do not need to be adjusted.

- Case C

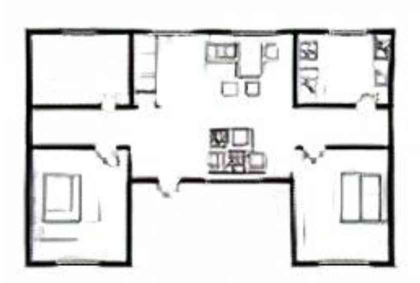
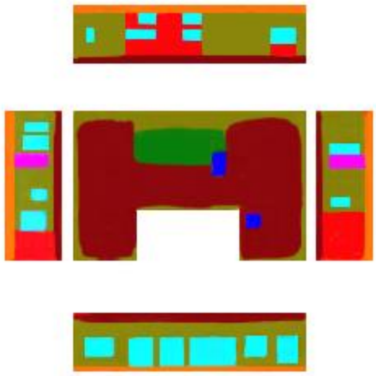



Figure 61. Solution P-C (left) and Solution F_H-C (right).

In Case C, no entry door is generated on the south elevation, but there is a more reasonable distribution of living rooms in the south direction in the plan generation results, indicating the need to change one of the floor-to-ceiling windows to an entry door on the south elevation of Solution F_H-C.

On the west elevation, a secondary entrance is generated, corresponding to the location of the equipment room on the plan, which can be directly accessed from outside. This is more convenient and reasonable than in Case B.

The entrance on the east elevation, on the other hand, corresponds to the location of the bathroom on the plan. This is an unreasonable point, and the entrance on the east elevation needs to be eliminated.

The windows generated by the rest of the elevation match well with the rooms on the plan and do not need to be adjusted. The photovoltaic and high windows on the roof are generated in reasonable positions and do not need to be adjusted.

Coupling Degree Subjective Analysis of AttU-net Generated Façades and Plans

- Case A

In the south elevation of Case A, the entrance door is generated in the bedroom position of the plan, but the corresponding entrance door is not generated in the living room position, so the generation position of the entrance door needs to be adjusted in Solution F_A-A.

Figure 62. Solution P-A (left) and Solution F_A-A (right).

The remaining elevations mainly generate windows, and the window positions match the rooms in the plan and do not need to be adjusted. A large number of photovoltaic panels are generated on the roof, and the location and size are reasonable, indicating no adjustment is needed.

- Case B

Figure 63. Solution P-B (left) and Solution F_A-B (right).

In the south elevation of Case B, same as Case A, the entrance door is generated in the left bedroom position, but not in the living room position, therefore it is necessary to adjust the generation position of the entrance door as well in Solution F_A-B.

The bedroom in the southeast corner has a door that allows direct access to the bedroom from the outdoors, which is common and reasonable in rural residences, and is consistent with the existing solution.

The windows on the rest of the elevations correspond to the rooms and do not need to be adjusted. A large number of photovoltaic panels and skylights are generated on the roof, and the skylights are mainly located in the living room, bedroom and kitchen, which can increase the light.

- Case C

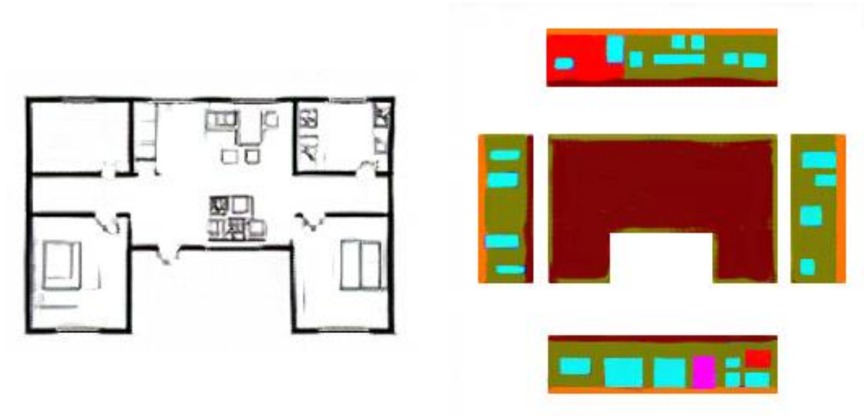


Figure 64. Solution P-C (left) and Solution F_A-C (right).

The south elevation in Case C, which generates the entry door at the location of the living room on the plan, has a reasonable shape and location and does not need to be adjusted for the entry door.

On the remaining elevations, the shape, size and location of the windows are reasonable and do not require adjustment. A large number of photovoltaic panels are generated on the roof, and the location and size are also reasonable and do not need to be adjusted.

In general, the generation of Case C is satisfactory and matches well with the plan, and no adjustment is needed.

7.4.1. Objective Analysis

Requirements for Direct Lighting

According to GB 50033-2013 "Design Standards for Lighting in Buildings", bedrooms, living rooms (halls) and kitchens of residential buildings should have direct lighting. When modeling the solutions generated by HRNet and AttU-net, it is found that all rooms can meet the requirements of direct lighting, and there is no need to adjust the windows in order to meet the lighting requirements.

Requirements for the Window-To-Wall Ratio

The window-to-wall ratio also needs to be calculated to evaluate whether it meets the code requirements. The above code points out that the building window-to-wall ratio is the ratio of the window opening area to the room façade unit area (i.e., the area enclosed by the building floor height and opening positioning line). At present, both residential buildings and public buildings, the window-to-wall ratio tends to increase.

The increase of window-wall ratio can get sufficient light and good view, but it also leads to the possibility of increased energy consumption for air conditioning in summer and heating in winter. In addition, since each wall has a different orientation, the amount of solar radiation obtained by the wall is also different, so the code has different requirements for the limit value of window-to-wall ratio for each orientation.

According to the Energy Conservation Design Standards for Residential Buildings in Cold and Severe Areas (JGJ 26-2018), the energy saving limit value for the window-to-wall ratio in the south direction is 0.6, 0.4 in the north direction, and 0.45 is required for the east and west direction. In this stage, the model is built by DesignBuilder to calculate the window-to-wall ratio, and the results for each orientation are obtained in the following Table 29.

Table 29. Window-to-Wall Ratio Results for Each Orientation

	Window-to-wall ratio of South	Window -to-wall ratio of North	Window -to-wall ratio of West	Window -to-wall ratio of East
Solution F_H-A	0.44	0.31	0.29	0.32
Solution F_H-B	0.06	0.19	0.22	0.36
Solution F_H-B	0.54	0.21	0.29	0.09
Solution F_A-A	0.28	0.32	0.19	0.16
Solution F_A-B	0.17	0.31	0.11	0.16
Solution F_A-C	0.48	0.42	0.21	0.27

It can be observed that most of the window-to-wall ratios generated by SD-GAN are within the limits and are more in line with the conventional design. However, there are a few cases that do not comply with the limits or have too small window openings, resulting in poor lighting.

In Solution F_A-C, the window-to-wall ratio in the north direction is 0.42, which exceeds the limit of 0.4.

In Solution F_H-B, the window-to-wall ratio in the south direction is only 0.06. In traditional building design, the south elevation is better lit, and the window-to-wall ratio needs to be larger in order to get good lighting.

Therefore, in the modification process, manual adjustment would be conducted to address these non-conforming and unreasonable window-to-wall ratios to get better results.

In summary, although there are some windows and doors on the façade that do not correspond well to the rooms in the plans, overall, the subjective matching is still relatively high, and only some fine-tuning of the façade is needed to obtain the combined model generated entirely by SD-GAN.

In the objective window-to-wall ratio calculation, 24 walls were performed, and 23 of them met the regulations, accounting for 95.8% of the total number following Equation (7-1. In addition, the reasonableness of the window-to-wall ratio of the walls should also be evaluated. 22 of them, or 91.7% of the total, met the codes and design experience following Equation (7-2.

$$R_{code} = {(1 - N_{u-code})}/{N_{wall}} \tag{7-1}$$

$$R_{design} = {\left[1 - \left(N_{u-code} + N_{u-experience}\right)\right]}/{N_{wall}} \tag{7-2}$$

From the number of walls with reasonable window-to-wall ratios, it can be concluded that the previously trained SD-GAN has achieved reasonably satisfactory results in generating window-to-wall ratios.

7.5. Collaborative Adjustment

7.5.1. Adjustment Principles

Through the subjective and objective evaluation in the previous section, it can be found that some of the design solutions generated by SD-GAN have deviations in the coupling of building plan and elevation, and there is also a non-compliance with the current design codes regarding the window-to-wall ratio. Therefore, appropriate adjustments need to be made to the above existing design solutions to make them conform to the requirements of each index. The following principles need to be followed when adjusting:

Considering integrity and consistency

When making the adjustment, the integrity and consistency of the building need to be considered comprehensively. The adjusted solutions should maintain the consistency between the plan layout, façade design and functional layout to ensure that the overall image and function of the building is maintained.

Complying with the Current Design Code

Ensure that the adjusted design solutions follow the existing building design codes and standards. This will ensure that the adjusted solutions are consistent with the current design in terms of compliance and feasibility.

Maintaining Comparability

To enable comparable energy simulation between the generated solutions and the existing solution, excessive adjustments should be avoided. Adjustments should try to maintain the basic layout, spatial functionality, etc. of the generated scenarios in order to ensure the validity and comparability of the results of the later simulation analysis. To facilitate the verification of SD-GAN's consideration of building energy efficiency in the process of generating solutions.

7.5.1. Adjustment Process

Case A

In Solution F_H-A, there is a secondary entrance at the bathroom position on the north elevation and a floor-to-ceiling window in the kitchen, which is not consistent with the subjective view. Solution M_H-A removes the door corresponding to the bathroom location, and the size of the kitchen window is adjusted to be consistent with the other windows.

In Solution F_A-A, the entry door was generated in the bedroom position generated instead of the living room. This mistake was corrected in Solution M_A-A (Figure 65).

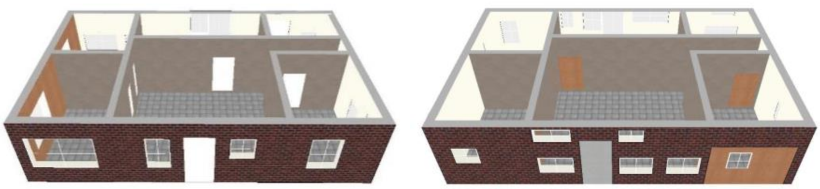


Figure 65. Solution M_H-A (left) and Solution M_A-A (right).

Case B

The position of the entrance door in the south elevation of Solution F_H-B is adjusted from the host bedroom to the living room. The windows on the south elevation of Solution M_H-B have been increased to the limits required by the current code to improve lighting in the living room and both bedrooms (Figure 66).

Same as Solution F_H-B, the position of the entrance door on the south elevation of Solution F_A-B is repositioned from the master bedroom to the living area in Solution M_A-B.

Figure 66. Solution M_H-B (left) and Solution M_A-B (right).

Case C

Solution F_H-C fails to generate an entry door on the south facing reasonable living room. Solution M_H-C has changed one of the floor-to-ceiling windows to an entrance door on the south elevation.

In Solution F_A-C, the window-to-wall ratio on the north elevation slightly exceeds the code limit. Solution M_A-C gives a correction (Figure 67).

Figure 67. Solution M_H-C (left) and Solution M_A-C (right).

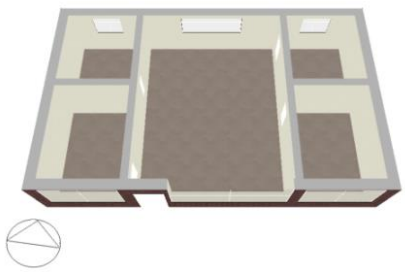
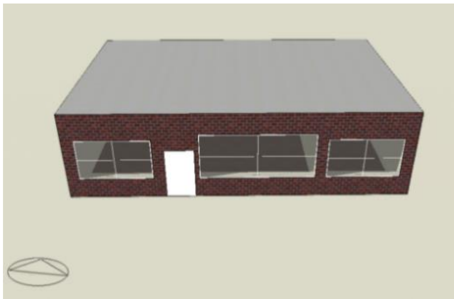
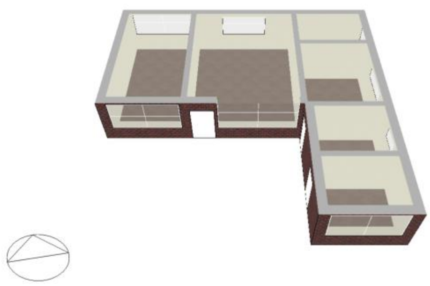
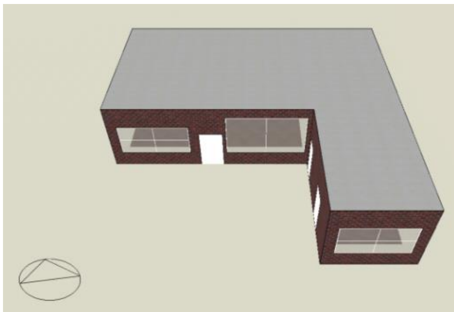
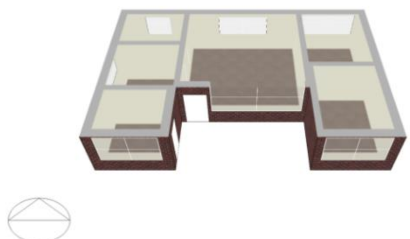
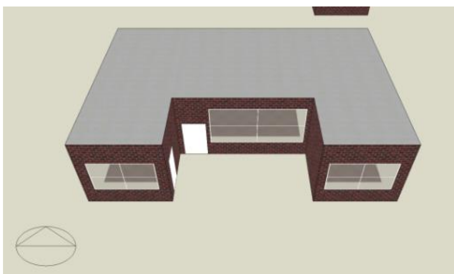
7.6. DesignBuilder Simulation

In this section, DesignBuilder is used to model the current situation, plan generation solutions, and combined plan and elevation generation solutions for each of the 3 cases, and the analysis results are discussed horizontally.

7.6.1. Simulation Modeling

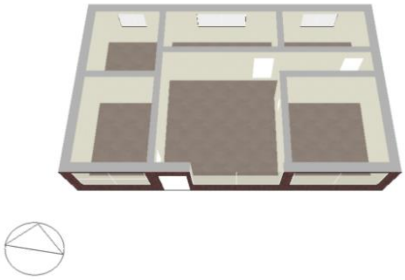
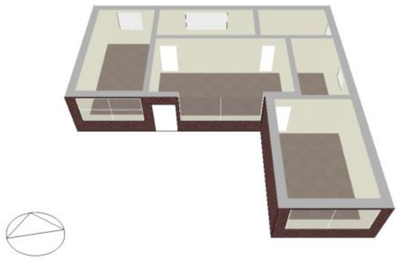
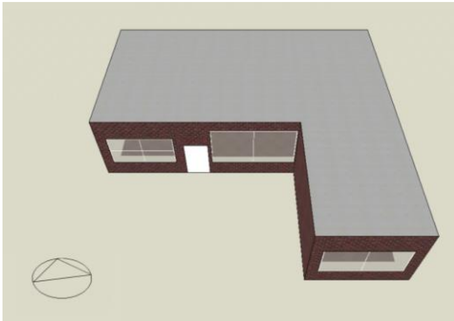
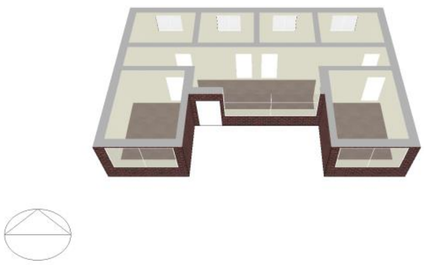
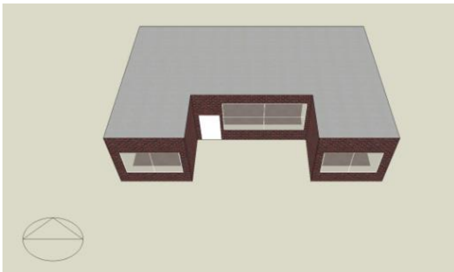
The current status of cases was modeled first, and the results are shown in the Table 30.

Table 30. Current Situation Modeling.

Item	Perspective (without roof)	Perspective (with roof)
Case A		
Case B		
Case C		

Subsequently, the generated plan solutions from Chapter 4 above are modeled as shown in Table 31.

Table 31. Generated Plan Solutions Modeling.

Item	Perspective (without roof)	Perspective (with roof)
Solution P-A		
Solution P-B		
Solution P-C		

Finally, the generated plan solutions are combined with the façade solutions generated by HRNet and AttU-net modified SD-GAN for modeling, respectively. In this process, the issues existing in section 0 above are presented before and after the model correction simultaneously. The manual correction results in matching the rooms of the plan with the façade solutions as closely as possible and complying with the requirements of the relevant codes (Table 32, Table 33).

Table 32. Generated Plan Combining HRNet Modified SD-GAN Solutions Modeling.

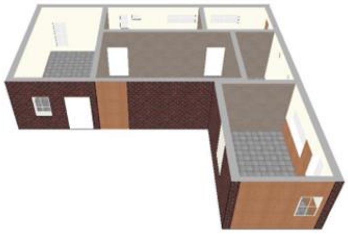
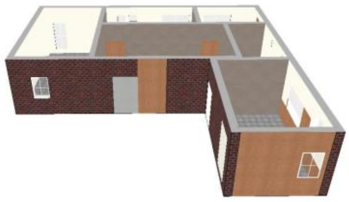
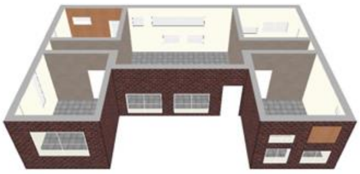
Item	Perspective (without roof)	Perspective (with roof)
Solution F_H-A		
Solution M_H-A		
Solution F_H-B		
Solution M_H-B		
Solution F_H-C		
Solution M_H-C		

Table 33. Generated Plan Combining AttU-net Modified SD-GAN Solutions Modeling.

Item	Perspective (without roof)	Perspective (with roof)
Solution F_A-A		
Solution M_ A -A		
Solution F_A-B		
Solution M_A-B		
Solution F_A-C		
Solution M_A-C		

7.6.2. Simulation Settings

In order to facilitate the cross-sectional comparison between the original and generated solutions, the following simulation parameters will be set uniformly based on the strategy in Section 3.4 above (Figure 68, Table 34).

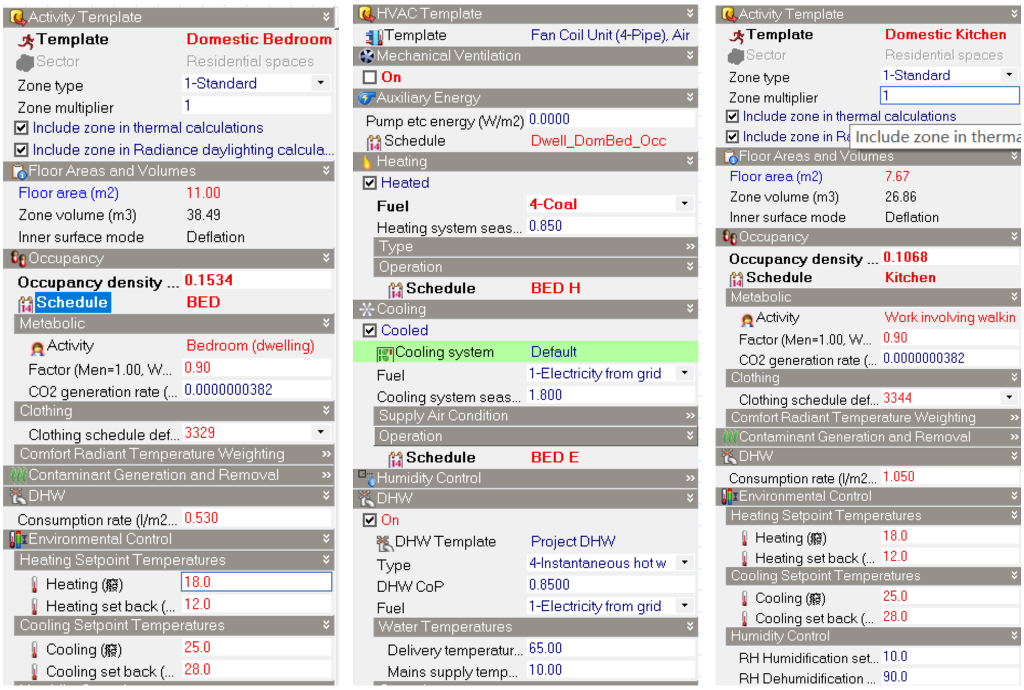


Figure 68. DesignBuilder Simulation Parameter Settings

Occupant Settings

Through the field investigation, there are 3 resident family members in Case A. The number of users in each room is as follows: 1 person in bedroom 1 and bedroom 2, 2 persons in the living room, and 1 person in the kitchen, bathroom and storage room. The number of Case B occupants is as follows: 1 person in bedroom 1 and bedroom 2, 2 persons in the living room, 1 person in the kitchen, bathroom and storage room. There are 2 resident family members in Case C. The number of occupants in each room is as follows: 1 person in each bedroom, 1 person in the living room, 1 person in the kitchen bathroom and storage room.

Indoor Thermal Perturbation Setting

5 W/m² for lighting and 3.8 W/m² for home appliance equipment. The calculated indoor temperature is 18 ℃, with 0.5 times of air changed per hour (ACH) of ventilation exchange.

External Envelope Settings

The envelope of the cases includes external walls, roofs, and external windows. The construction method and film coefficients of each part are shown in Table 34. For façade generation, appropriate adjustments will be made based on the results of façade generation. In principle, the state of the existing building will be held as much as possible to control the variables more effectively.

Table 34. Construction Method and Film Coefficient of The Envelope.

Item	Construction Method	Film Coefficient (W/m^{2}K)
External Wall	370 mm clay brick + 20 mm cement	1.54
External Window	aluminum framed glazing	6.18
Roof	100 mm concrete + 40 mm cement	1.86
Timber External Wall	Exterior Wall + Panel (Exterior Wall + Wood Wedge + Asphalt + Linoleum + Studs + Timber Panel)	1.38

Basis of Simulation Calculation

The remaining parameters were set according to the building thermal design criteria of GB 50716-93 “Thermal Design Code for Civil Buildings”, and the epw meteorological data of Beijing were used for analysis.

7.6.3. Simulation Results

All of the above models were simulated in DesignBuilder for energy consumption, and the results are summarized in Table 35.

Table 35. Energy Consumption Simulation Results.

Item	Annual Heating Consumption （kW · h）	Annual Cooling Consumption （kW · h）	Total Annual Energy Consumption （kW · h）	Generated Power （kW · h）	Balanced Total Annual Energy Consumption （kW · h）
Case A	11375.03	2276.10	16380.14	-	16380.14
Solution P-A	9578.11	2055.39	14188.26	-	14188.26
Solution M_H-A	12132.11	1757.27	15346.3	10240.36	5105.94
Solution M_A-A	11162.96	1635.79	16088.67	10240.36	5848.31
Case B	15350.27	2701.41	20608.09	-	20608.09
Solution P-B	12766.55	2364.34	17982.44	-	17982.44
Solution M_H-B	13311.51	2278.77	18149	9167.92	8981.08
Solution M_A-B	13040.89	2127.53	17326.13	9167.92	8158.21
Case C	11488.38	1969.11	15686.90	-	15686.90
Solution P-C	10407.48	1968.44	14515.83	-	14515.83
Solution M_H-C	11681.95	1703.66	15073.27	6536.52	8536.75
Solution M_A-C	11957.35	1864.02	14430.89	8417.68	6013.21

7.6.4. Results Discussion

Annual Heating Energy Consumption

From the simulation results of the annual heating energy consumption, the values of the building heating energy consumption are lower for the solutions with changes to the floor plan only compared to the prototype of the case. However, when the building façade in the project prototype is replaced with the generated building façade, the heating energy consumption increases and decreases compared to the project prototype. After observing the experimental and the original façade, it was found that the window openings of the new façade were increased. Some changes were also made to the window openings, especially since a large number of windows were generated on the north-facing wall. The increase of north-facing windows may be the direct cause of the increase of heating energy consumption of the solution.

By calculating the ratio between the increase and decrease of heating energy consumption, Solution P-A reduces the energy consumption by 15.8% compared to the case prototype. Solution M_A-A decreases by 1.8%; the heating energy consumption of Solution M_H-A is increased by 6.7%. The energy consumption reduced by Solution P-B is 16.8%; Solution M_A-B is reduced by 15.0%; Solution M_H-B is 13.3%. The energy consumption reduced by Solution P-C is 9.4%; the heating energy consumption of Solution M_A-C is increased by 4.1%; and the heating energy consumption of Solution M_H-C is also increased by 1.7% (Figure 69).

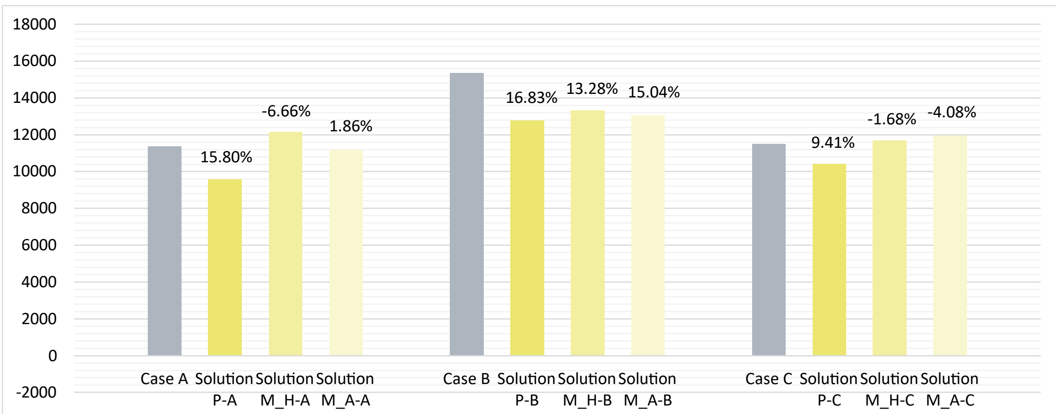


Figure 69. Annual Heating Energy Consumption Simulation Results (kW · h).

A total of 6 models were built for the HRNet generating network and AttU-net generating network used in this study. After the energy consumption simulations, the annual heating energy consumption decreased in 3 of them, accounting for 50% of the total number of models.

The observation and analysis of the façade generation results reveal that in Solution M_H-A, the generated windows are more fine-grained and the overall window opening area has increased compared to the case prototype. This point may be the reason for the higher heating energy consumption in it. The heating energy consumption of Solution M_H-C and Solution M_A-C is also increased compared to the prototype. After analysis, it may also be related to the increase in window opening area and the volume factor of the case itself.

Annual Cooling Energy Consumption

The simulation results of the annual cooling energy consumption show that the cooling energy consumption is generally lower for the plan only alteration solution compared to the prototype of the case. When the building façade in the project prototype was replaced with the generated building façade, the cooling energy consumption was reduced compared to the prototype and also compared to the plan only alteration solution. This result shows that the new façade solution has a remarkable effect on the reduction of cooling energy consumption. The reduction in cooling energy consumption can lead to an effective reduction in the total annual energy consumption of the building (Figure 70).

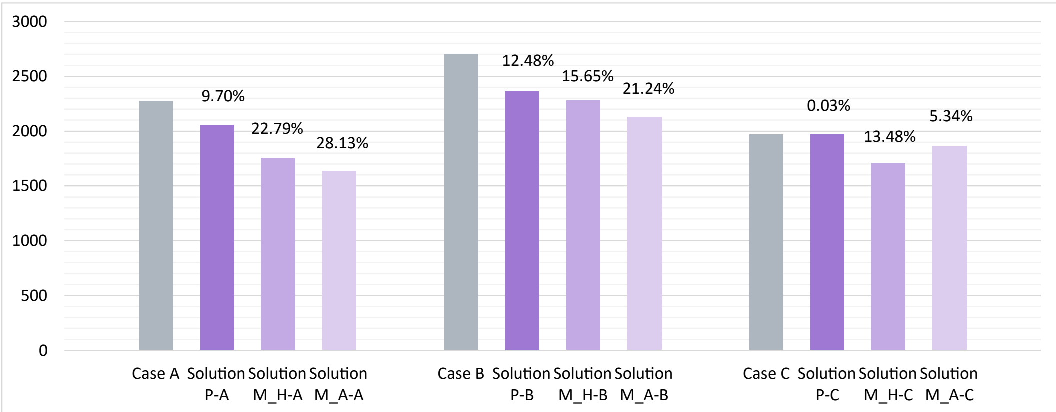


Figure 70. Annual Cooling Energy Consumption Simulation Results (kW · h).

By calculating the percentage reduction of annual cooling energy consumption, the cooling energy consumption of Solution P-A is reduced by 9.7% compared to the prototype; the percentage reduction of cooling energy consumption of Solution M_A-A is 28%; and the reduction of Solution M_H-A is 22.8%. The percentage decrease in cooling energy consumption for solution B-P was 12.5%; Solution M_A-B decreased by 21.2%; Solution M_H-B decreased by 15.7%. The cooling energy consumption of Solution P-C is basically the same as the prototype; the percentage decrease of cooling energy consumption of Solution M_A-C is 5.3%; and the decrease of Solution M_H-C is 13.4%.

After the energy consumption simulation, there are 6 models with 100% reduction in cooling energy consumption for the whole year. Solution M_A-A and Solution M_H-A and Solution M_A-B have a relatively high percentage of reduction in annual cooling energy consumption, and Solution M_A-C has a smaller percentage of reduction.

Total Annual Energy Consumption

The simulation results of the total annual energy consumption of the building show that the solution with only changes to the floor plan shows a slight reduction in total annual energy consumption compared to the prototype of the case. After replacing the building façade in the prototype with the generated building façade, it can be seen from the figure that the reduction in the total annual energy consumption of the building is larger. This is due to the fact that most of the roofs in the training dataset used are set up with photovoltaic panels for photovoltaic power generation. And SD-GAN learns this dataset with the building block of roof photovoltaic for learning and generation. Thus, the new façade generation solutions generate a large number of PV panels on all the roofs, which can provide a large amount of PV power to the building, leading to a large reduction in the total annual energy consumption of the building.

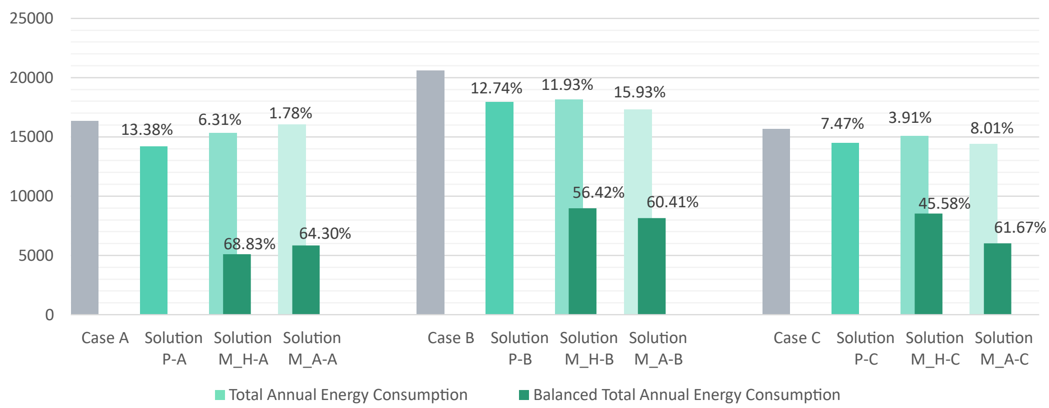


Figure 71. Total Annual Energy Consumption Simulation Results (kW · h).

By calculating the percentage reduction of annual cooling energy consumption, the percentage decrease of solution A-P is 13.4%; the percentage decrease of solution A-Ac is 1.8%; and the percentage decrease of Solution M_H-A is 6.3%. The percentage of decrease in total annual energy consumption of solution B-P building is 12.7%; Solution M_A-B is 15.9%; Solution M_H-B is 11.9%. The percentage decrease in total annual energy consumption for Solution P-C buildings is 7.5%; Solution M_A-C decreases 8.0%; and Solution M_H-C 3.9%.

After the energy consumption simulation, the total number of models with a decrease in total annual energy consumption is 6, or 100%. However, despite this, 4 of the 6 models performed lower than the models based on generated plans, due to the impact of the annual heating energy consumption.

At the meanwhile, since all models generate a large number of PV panels on the roof, which can provide a large amount of photovoltaic power generation, the percentage of total annual building energy consumption decrease is very large for all 6 models in this study, basically above 50%. From the simulation of the balanced total annual energy consumption of the building, the percentage reduction of the newly generated solutions is all very large. Compared with the prototype, the percentage decrease of solution A-P is 13.3%; the percentage decrease of solution A-Ac is 64.2%; and the percentage decrease of Solution M_H-A is 68.8%. The percentage of decrease in total annual energy consumption of solution B-P building is 12.7%; Solution M_A-B is 60.4%; Solution M_H-B is 56.4%. The percentage decrease in total annual energy consumption for Solution P-C buildings is 7.5%; Solution M_A-C decreases 61.6%; and Solution M_H-C 45.5%.

In general, it is promising that SD-GAN can obtain more significant energy efficiency gains by simply adjusting the distribution of rooms and the reorganization of building components during the generation of solutions. The performance of the elevation-dependent generated models is not stable, and most of them can perform better than the plan-dependent generated models when the effect of PV panels is excluded, although not much. But the ability to provide richer inspiration for architects is perhaps the more attractive aspect.

7.7. Summary

This chapter demonstrates a relatively complete architectural design process through an empirical study, including a series of " Generation - Evaluation - Adjustment - Simulation" steps. This process aims to verify the feasibility and validity of architectural design solutions obtained through human-AI collaboration. The results of the empirical study are important for exploring the potential and contribution of human-AI collaborative architectural design.

In this stage, the results generated by the trained neural network are verified by selecting 3 ordinary houses in Jianchang Village, Beijing as real cases with examples. In this phase, SD-GAN generated 9 solutions. The coupling degrees of them were compared by subjective and objective comparisons, respectively.

The results show that the SD-GAN-generated plan and façade coupling is subjectively positive, with an objective plausibility of over 91%. This indicates that the building solutions generated by SD-GAN complement each other in the design of plan and façade with good integrity and coordination.

After being simply modified according to the design codes and basic requirements, further energy consumption simulation analysis was performed. It was found that the balanced total energy consumption of the SD-GAN-generated model decreased significantly throughout the year, basically above 50%. This is directly related to the generated building roofs designed with a large number of solar PV panels. This indicates that the SD-GAN-generated low-rise building solution has potential advantages in terms of energy consumption and is expected to reduce the energy consumption of the building.

Specifically, in terms of annual cooling energy consumption, the SD-GAN-generated building solutions show varying reductions in energy consumption, ranging from 5% to 28%. The annual heating energy consumption, on the other hand, shows a variable trend of rise and fall. This is related to the increase in heat loss in winter due to the addition of many windows on the north side wall. This indicates that there is some potential for improvement in the energy consumption of the SD-GAN-generated building solutions, especially in the stability and effectiveness of the cooling and heating energy consumption.

In general, the solutions generated by SD-GAN show lower energy consumption levels in terms of total energy consumption throughout the year, as well as richer and more diverse façade designs with more subjective aesthetics. This indicates that SD-GAN is able to balance energy consumption and aesthetics when generating low-rise building solutions. It also demonstrates the potential and effectiveness of human-AI collaboration in the architectural design solution generation. By combining AI generation and human adjustment, innovative, feasible and energy-optimized building design solutions can be obtained.

However, at the same time, the issues of unstable cooling energy reduction and less-than-optimal heating energy performance cannot be ignored. Therefore, in future intensive training, the above issues need to be paid attention to, and further improve and optimize the low-rise building solutions generated by SD-GAN to achieve a better combination of energy performance and aesthetics.

Chapter 8. Conclusions

The integration of AI in sustainable architectural design presents a myriad of challenges and opportunities. Continuous learning and innovation are essential for architects to take advantage of advances in AI technology. Architects should keep an open mind and continue to adopt new technologies and approaches as the field evolves. By keeping abreast of the latest AI advances, architects can incorporate cutting-edge technologies into their design process and explore innovative sustainable building design ideas. This adaptive thinking enables architects to meet evolving market demands and societal requirements in a changing environment.

As discussed in the Preface, this research aims to explore how AI technologies can empower sustainable architectural design and address the outlined research objectives. In this final chapter, a comprehensive summary of the research findings is presented and future prospects for further advancing the field are outlined.

8.1. Approaches Toolbox

"The Approaches Toolbox" serves as a framework for identifying AI technologies used in various research areas and exploring their strengths, weaknesses, and potential for sustainable architectural design. This approach guides researchers in understanding the different applications of AI technologies and identifying the most appropriate technologies for specific research objectives.

"Which AI technologies are employed in which research fields or orientations?"

"Within the same field, are there any advantages or disadvantages in the application of the technologies?"

To answer these first two questions in Section 1.4 on "Approaches Toolbox", we constructed a 3-level matrix search method in Chapter 2, and collected 621 articles on CumInCAD, a pioneering academic platform, to analyze the intelligence in terms of research domain, research trend and regional division, task distribution, and algorithm distribution. The correlation analysis between 14 tasks and 29 algorithms was also summarized in depth (Table 6). This result may provide a reference for AI applications in the broader construction field.

First, by analyzing the research domains and research trends, we can understand the current hot spots and trends of AI applications in the construction field, thus providing guidance for future research directions and application scenarios. Secondly, through the study of regional division, we can understand the research characteristics and focus of different regions in the construction field, which provides strong support for cross-regional cooperation and communication. Finally, through the analysis of algorithm and task distribution, we can understand the application and development trend of different algorithms in the construction field, so as to provide reference for the selection and optimization of algorithms.

" What are the potentials or possibilities of AI technology implementation in terms of sustainable building design?"

For the third question, we found that among the many applications of neural networks, the use of generative adversarial networks (GANs) as an image processing tool has recently been of interest to visual artists and computational designers. At the time of writing Midjourney and DALL-E, AI programs that create images based on textual descriptions represent a popular topic among architecture students worldwide. Currently, all GAN-generated art is two-dimensional, but experiments in three-dimensions are underway - a crucial development for architectural purposes. For architectural design, ArchiGAN based on

CycleGAN and Pixe2Pix has demonstrated the potential of GAN for building plan generation. However, three critical issues remain to be addressed in this field of research.

Based on this, the study developed a corresponding research strategy in in Chapter 3,

- Lack of Energy Concern

Introducing SD competition entries that emphasize energy efficiency and sustainability to empower the samples. And naming the model trained with them as SD-GAN. It is hoped that this approach could help the network model constructed in this study to perceive the methods and logic of targeted architectural design and improve the energy efficiency performance of the generated results.

- Low Capability Dealing with Complicated Demands

Applying data augmentation and generator replacement in different scenarios to purposefully enhance the generative power of SD-GAN to cope with more complex task requirements. This requires it to identify and generate more building features and building components based on a richer observation of the buildings' exterior profiles.

- Do Not Have Comprehensive Implementation in a Complete Project

Conducting an empirical study on 3 different shape cases of Jianchang Village in Beijing, including: building plan generation, façade generation, and the corresponding energy consumption simulation and comparative analysis. The empirical study will be implemented to validate the potential of collaborative human-AI architectural design.

8.2. Approach Construction

The construction of a neural network is a critical stage in the research process. Careful consideration must be given to the selection of training samples, the evaluation of training results, and the necessary improvements or modifications to ensure the effectiveness of the neural network. This process ensures that the generated design solution is consistent with the intended research goals. This stage of the research implements the first 2 strategies proposed for the current research gaps.

Strategy 1 – Empowering Samples

In the field of image generation, supervised learning AI neural networks are currently an efficient choice. The key to this approach is how to set and organize the training samples, as the quality of the training samples has an important impact on the performance of the model. The ensuing question is:

"What kind of samples should be employed for training?"

To answer this question, this study discusses the specific method of selecting world-renowned SD competition entries as training samples in Chapter 4 by implementing the 1st strategy. Since these entries come from universities and research teams around the globe, there is a diverse distribution of form types and technical characteristics. Different data may have different ranges of values and data distributions, which can greatly affect the training and prediction of the model. Therefore, normalization of data is an important step that can help us map the data to a uniform range, eliminate the quantitative differences between different features, and make the model more stable and accurate.

In this chapter, 3 principles for processing SD competition entries as training samples are established: Uniform Drawing, Uniform Annotation, and Uniform Labeling. This can effectively solve the problem of inaccurate or unrepresentative training sample labels that may exist in the field of image generation, thus providing a reliable database for subsequent research and practice.

Strategy 2 – Improving Generating Capability

The following two questions guide the implementation of the strategy to improve the generative capacity in the next Chapter 5 and Chapter 6, which is still unsatisfactory for architectural design.

"How will the training results be verified or evaluated?"

"If the training results do not meet the requirements of the study, how can they be improved or modified?"

- Preliminary Training

In the preliminary training in Chapter 5, SD-GAN is divided into 2 models for training, where Model 1 focuses on the generation of FSL and Model 2 on the generation of BFP. Model 1 was evaluated in terms of spatial allocation, functional distribution, and edge clarity of the generated results. Model 2 was evaluated in terms of wall and furniture generation accuracy.

The results show that the performance of Model 1 is not satisfactory, with an average score of 2.25 for CSA and CCB and 1.875 for RFD. Model 2 performs better, with high scores of 4.875 and 4.375 for WGA and FGA, respectively.

These evaluation results suggest the weaknesses of SD-GAN in preliminary generating FSL. Although it performs better when dealing with image pairs with relatively simple mapping relationships, there is a certain lack of learning ability when dealing with complex mapping relationships in such a small number of samples.

- Data Augmentation

In order to solve the above problems of Model 1, data augmentation experiments are carried out. The data augmentation was performed on the training set of 90 data using rotate and flip operations, which effectively improved the generalization ability and robustness of the model. all the indexes of Model 1 were improved to the ideal state: CSA score of 4.875, CCB score of 4.25, and RFD score of 4.625, and the performance of the model was also more stable.

This experiment result fully illustrates the feasibility of expanding the dataset by geometric transformation method to improve the learning ability. Through data augmentation, more training samples can be generated, which can help the model to better learn the features and patterns in the data and improve the generalization ability of the model, i.e., it performs well on new data.

- Generator Replacement

To further enhance the ability to learn more challenging and complex mapping relationships, in the façade generation experiments in Chapter 6, different generation networks were tried to replace U-net in SD-GAN, including U-net++, HRNet, and AttU-net.

To evaluate the generation results, both subjective and objective evaluations were used in this stage, which are subjective scoring and SSIM (structural similarity) judgment. Through the comprehensive evaluation of the generation results of the above 4 types of generative networks, the results show that, compared with other generative networks, AttU-net performs better in terms of both subjective scores and SSIM values. In addition, the evaluation results show that HRNet is another acceptable choice. Although the subjective score of its generation results is slightly lower than AttU-net (7%) and the SSIM value is slightly lower than AttU-net by 6%. However, considering that HRNet can save about 25% in training time, it is a worthy option to consider in scenarios where fast training and generation are required.

The results of this experiment have important implications for further research and application of façade generation. It should be noted that although AttU-net and HRNet perform better in the experiments, the selection of generative networks may vary for different tasks and datasets, and therefore should be chosen according to the actual situation in specific applications.

8.3. Approach Validation

Approach validation is the implementation of the 3rd research strategy proposed in this study。 And need to answer the following 2 questions：

"What kind of simulation tools are used for validation?"

"Which variables should be controlled in the validation process?"

Strategy 3 – Empirical Study

This strategy is implemented in Chapter 7 through a series of " Generation-Evaluation-Adjustment-Simulation" stages. This process aims to verify the feasibility and effectiveness of the architectural design solutions obtained through the human-AI collaborative process.

In generation stage, 3 cases in Jianchang Village, Beijing, China were selected for SD-GAN to generate floor plans and façade. Both HRNet and AttU-net were employed in this process to facilitate later simulations and comparisons. This stage obtained 3 groups of generated results, including floor plans, façades generated by HRNet, and façades generated by AttU-net, for a total of 9 results.

In evaluation stage, the coupling of the generated results was thoroughly verified to ensure the coordination and consistency of the generated design solutions in different design dimensions. The subjective evaluation compared the generated building plan and corresponding elevation results based on the 3 cases and recorded the incompatible parts. The objective evaluation examined and recorded the generated solutions according to the current building codes. The results show that the SD-GAN-generated plan and façade coupling is subjectively positive, with an objective plausibility of over 91%.

In adjustment stage, human corrections were carried out to address the above issues. In order to ensure comparability of results, the adjustment is performed according to 3 principles: considering integrity and consistency, complying with the current design code, and maintaining comparability. Ultimately, 3 groups of models were obtained that could be used for comparison: models generated by relying on plans only, models generated by mixing plans and HRNet facades, and models generated by mixing plans and AttU-net facades, for a total of 9 models.

In simulation stage, energy consumption simulations of all the obtained design models were performed by DesignBuilder to verify the stability, reliability, and energy efficiency of the SD-GAN generated solutions. This stage allows a more objective performance assessment of them. In this stage, the parameters of building materials, thermal conductivity, insulation thickness of each building component, as well as the heating, ventilation, air conditioning and lighting methods of the building were further set consistently with the original case, to express the SD-GAN generation effect as much as possible.

The results showed that the annual cooling energy consumption was reduced from 5% to 28%. In contrast, the SD-GAN did not perform as significantly in terms of annual heating energy consumption due to the increased heat loss in winter caused by the addition of windows on the north wall. This indicates that the energy consumption of the SD-GAN still has some potential for improvement. Thanks to the generated building roofs designed with a large number of PV panels, the balanced total annual energy consumption of the mixed models was significantly reduced, generally above 50%. In this regard, the advantages of SD-GAN in generating devices for reducing energy consumption can be verified.

The complete process of collaborative human-AI architectural design with the aid of AI technology is presented simultaneously through the empirical study. This process demonstrates the potential for designers to work closely with AI technology to generate, evaluate, and modify architectural design solutions. It demonstrates the ability of AI technology to act as a design copilot, able to provide data support, algorithmic optimization, and design advice to help designers make decisions and create. Designers, in turn, have the opportunity to gain greater creative freedom to integrate their expertise and creativity into the design process to achieve better design outcomes.

8.4. Limitations

This study explores SD-GAN, a generative adversarial network-based approach to architectural design, with the aim of advancing the paradigm shifting in human-AI collaborative efforts to achieve sustainable architectural design. Currently, SD-GAN is capable of generating architectural design solutions with energy efficiency and sustainability features, providing designers with creative and feasible solutions. However, despite its potential and advantages in sustainable building design, there are still some limitations and challenges to overcome.

Limited Design Scope

SD-GAN is currently limited to generating single-story residential buildings. The number of floors and types of buildings are still limited. Therefore, there is a need to further extend the design capability of SD-GAN so that it can generate more types of architectural design solutions.

Lack of Spatial Constraints

Architects place more emphasis on the abstract concept of " Space" in the architectural design process. However, the current SD-GAN model focuses on the exterior features of the building and does not adequately consider the design and layout of the interior space. Therefore, it is necessary to explore the incorporation of interior space information into the SD-GAN generation process to achieve a more detailed and complete architectural design. This could be achieved by establishing interior space layout rules and constraints and incorporating the architect's expertise into the SD-GAN model.

Missing 3D Information

SD-GAN is still limited to generating two-dimensional images and remains challenging for generating architectural designs with three-dimensional volumes. Therefore, there is a need to investigate how to extend the training of SD-GAN from "pixels" to include "voxels" of building elements in order to provide more realistic and visualized architectural design results.

Unstable Energy Efficiency Performance

The performance of SD-GAN in terms of heating energy consumption is still not satisfactory. There is a need to further improve the sample quality and explore sample processing methods with more explicit indication of building orientation to improve the energy efficiency performance of the generated design solutions.

In future research, strategies such as extending the design scope, introducing internal space constraints, integrating voxel information, and improving energy efficiency will be used to further develop and improve the application of SD-GAN to achieve more comprehensive and efficient sustainable building design generation.

8.5. Outlook

8.5.1. The Architectural design Paradigm is Shifting

AI will change the current architectural design workflow, which could be a paradigm shift towards human-AI collaborative architecture.

From Linear to Non-Linear

The traditional architectural design workflow is a linear process, from concept to proposal to construction drawings, with fixed inputs and outputs at each stage, making it difficult to provide feedback and make changes. AI, on the other hand, enables a non-linear workflow that can be adjusted and optimized at any stage through real-time data analysis and model updates, increasing the flexibility and iterative nature of design.

From Single to Multiple

The traditional architectural design workflow is a single process, completed by one or a few designers, making it difficult to take into account the needs and interests of multiple parties. AI, on the other hand, enables a pluralistic workflow that can meet diverse needs and preferences by interacting and collaborating with multiple users, experts, collaborators, etc., improving the inclusiveness and synergy of design.

From Planning to Generation

The traditional architectural design workflow is a planning process in which designers develop design solutions based on their own knowledge, experience and creativity, making it difficult to break through their limitations and biases. AI, on the other hand, can realize the workflow of generation and generate design solutions through technologies such as machine learning and deep learning, which can expand designers' thinking and imagination and improve the innovation and diversity of design.

8.5.2. Impact on the Architecture Industry

As a way to use AI technology to assist, optimize and innovate the architectural design process, it can unleash the creativity of architects by leaving the strong computational and logical part of design to AI. Within the limited scope of visualization, the development of human-AI collaborative architectural design may be able to be carried out in the following fields:

Spatial Layout Issues

AI will be able to automatically generate or optimize spatial layout solutions, such as house plans and parking arrangements, based on given conditions and goals.

Urban Prediction Models

AI will be able to use big data and machine learning to predict various indicators in the city, such as population, traffic, energy consumption, environment, etc., to assist designers or city operators to improve the urban environment.

Mapping out Drawings

AI will be able to automatically generate or optimize drawing solutions, such as colorful general drawings, structure design drawings, mechanical and electrical pipeline drawings, etc., based on the architectural design knowledge database to ensure drawing quality and shorten the design period.

Intelligent Generation

AI will be able to generate architecture solutions of different styles, forms or functions, such as building appearance, landscape design, interior decoration, etc., based on user input or preference to improve design creativity and diversity.

8.5.3. Impact on Architecture Education

Human-AI collaborative architectural design is an inevitable trend and an opportunity to benefit the architecture industry. As we can find out from the previous section, AI is not the opponent of architects, but the partner of architects, which can help architects improve their professionalism and competitiveness. The future of architecture education should perhaps think about how to adapt to changes in the following aspects:

Data Acquisition and Processing

Teach how to effectively collect, organize, label, store and share architectural design-related data, such as drawings, models, parameters, specifications, etc., to facilitate AI training and application.

Model Development and Optimization

Teach how to build and improve AI models applicable to architectural design problems, such as neural networks, genetic algorithms, reinforcement learning, etc., in order to improve AI accuracy, stability and generalization.

Application Scenarios and Evaluation Metrics

Teach how to analyze and define different architectural design application scenarios and requirements, such as spatial layout, urban prediction, plotting and mapping, intelligent generation, etc., and the corresponding evaluation metrics, such as efficiency, quality, creativity, sustainability, etc., to assess the performance and effectiveness of AI.

Technical Regulation and Ethical Guidelines

Teach how to participate and promote the establishment of technical regulations and ethical guidelines for AI in the field of architectural design, such as data security, intelligence property, responsibility attribution, and social impact, in order to guarantee the legality, rationality, and ethics of AI.

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Appendix A - SD-GAN Raw Dataset I

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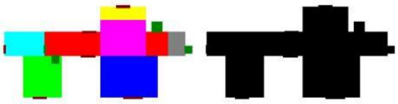
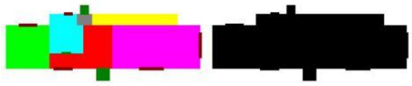
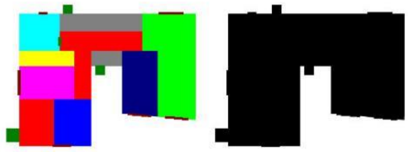
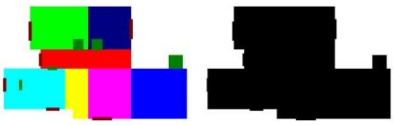
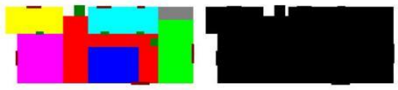
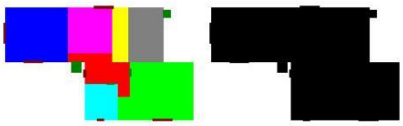
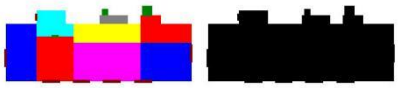
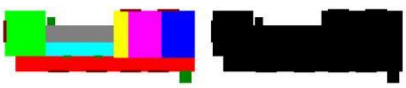
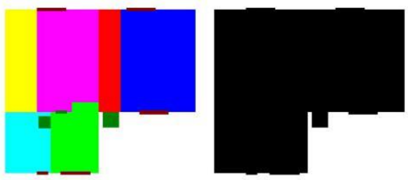
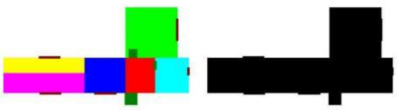
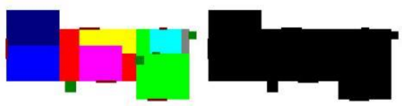
07-01		07-03	
07-04		07-05	
07-06		07-7	
07-09		07-13	
07-14		07-15	
07-16		07-17	

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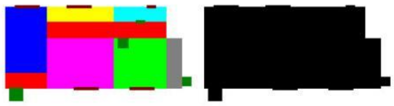
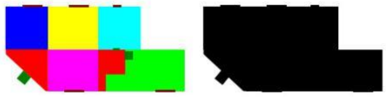
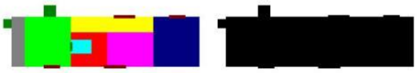
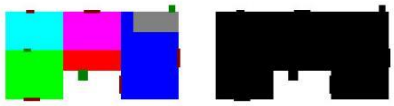
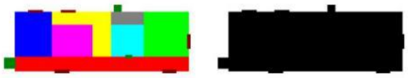
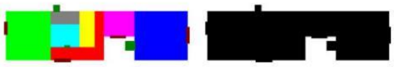
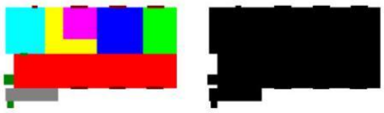
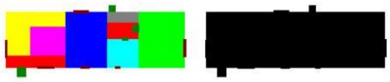
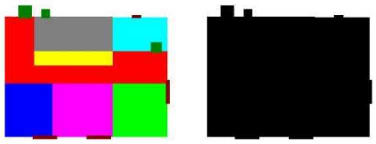
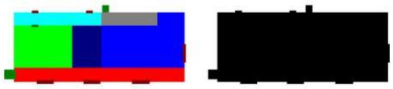
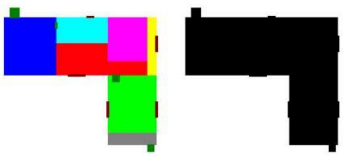
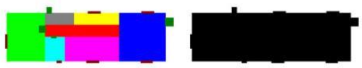
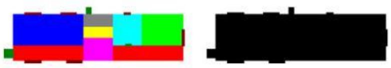
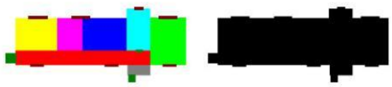
07-18		07-19	
07-20		09-2	
09-03		09-04	
09-06		09-09	
09-10		09-13	
09-14		09-15	
09-16		09-17	

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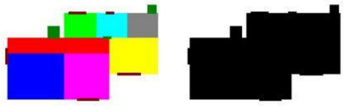
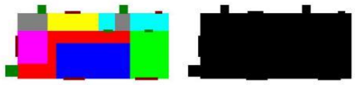
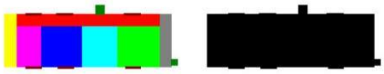
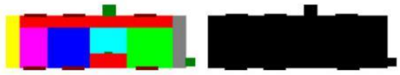
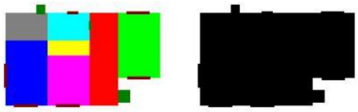
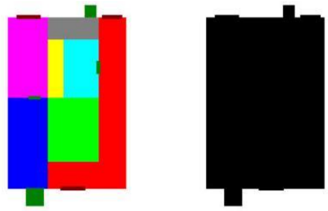
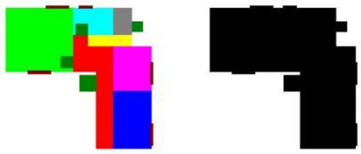
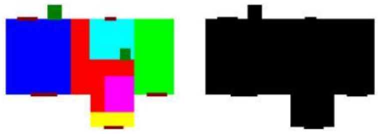
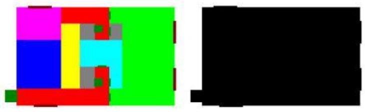
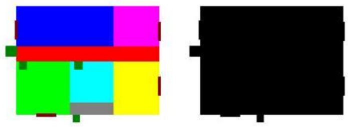
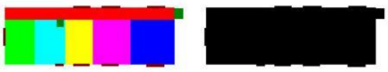
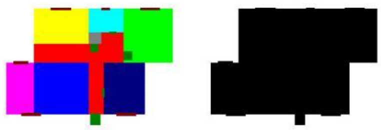
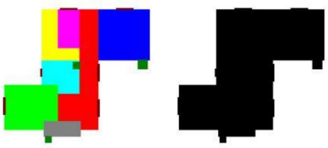
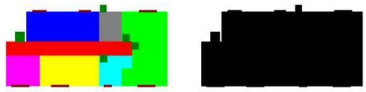
09-18		09-19	
09-20		10-1	
10-02		10-04	
10-11		10-13	
11-01		11-03	
11-04		11-05	
11-06		11-07	

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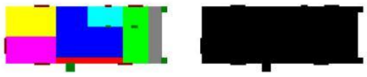
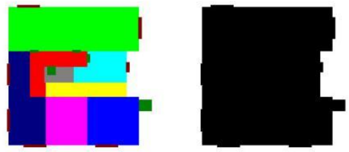
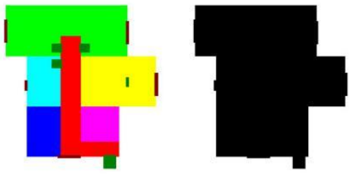
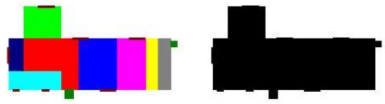
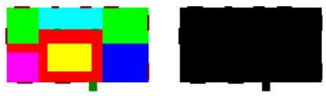
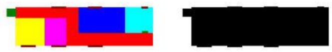
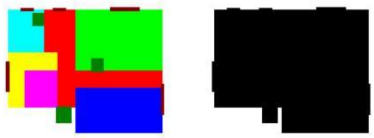
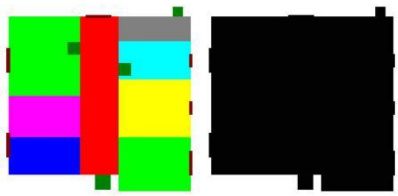
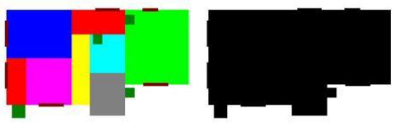
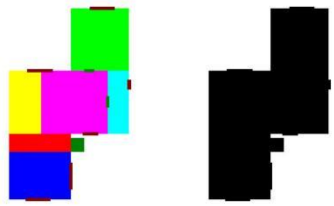
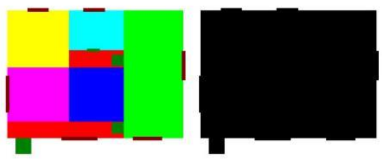
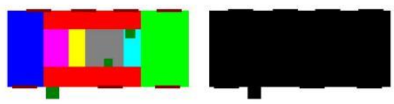
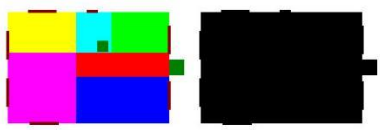
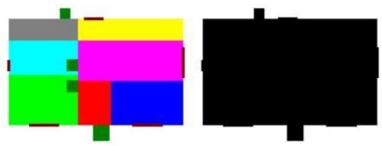
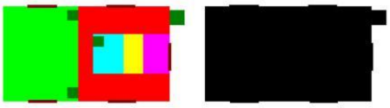
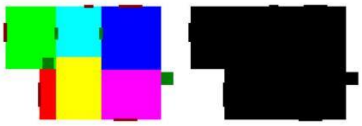
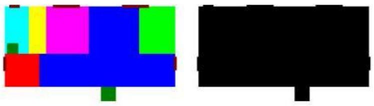
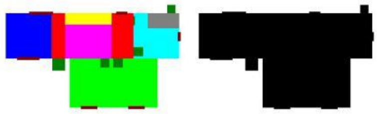
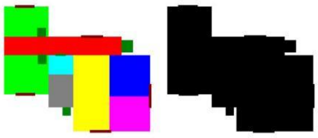
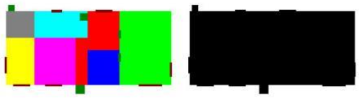
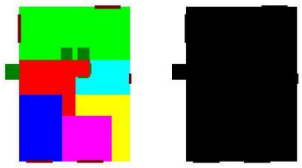
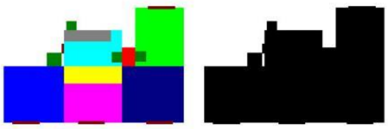
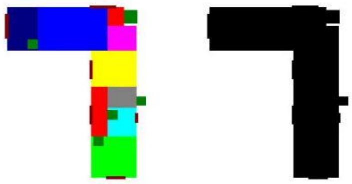
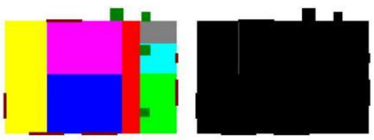
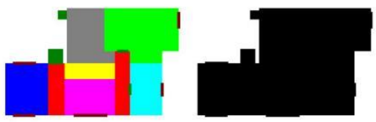
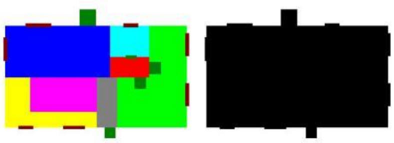
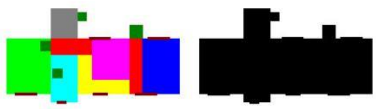
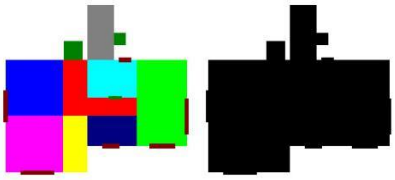
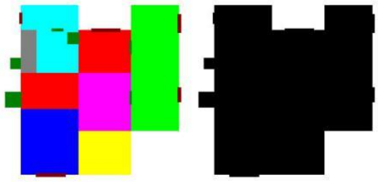
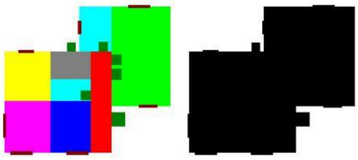
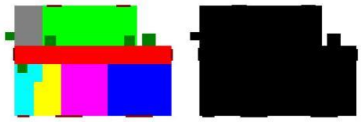
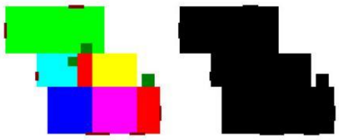
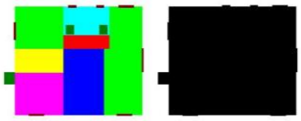
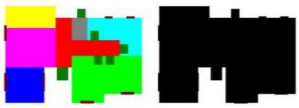
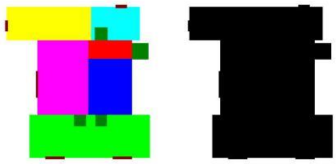
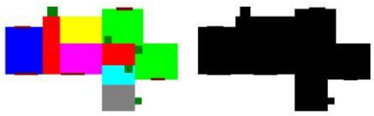
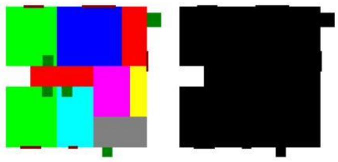
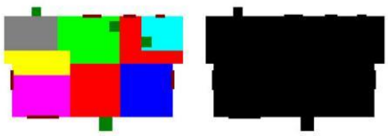
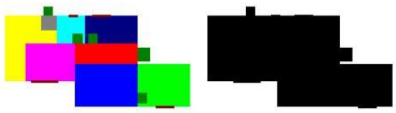
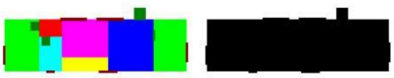
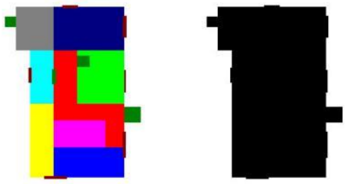
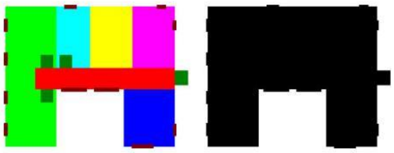
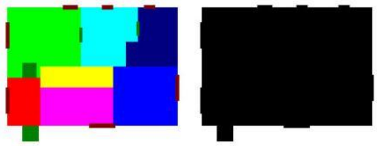
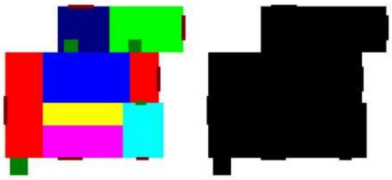
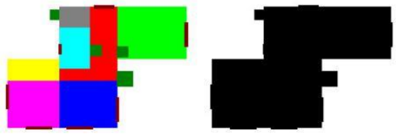
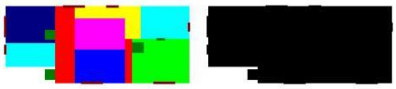
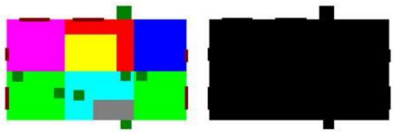
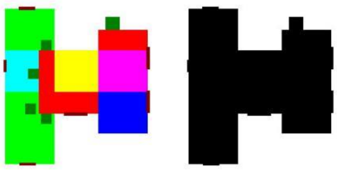
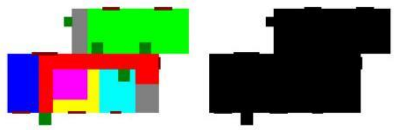
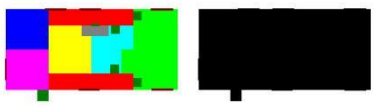
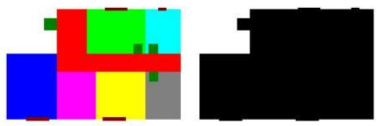
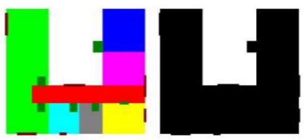
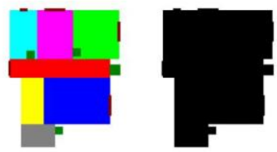
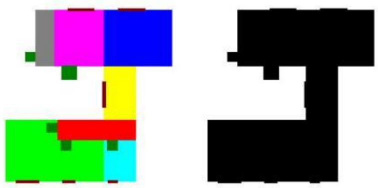
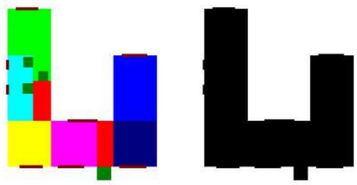
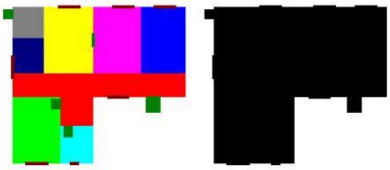
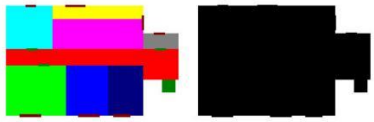
11-09		11-10	
11-12		11-15	
11-16		11-18	
11-19		12-01	
12-03		12-04	
12-09		12-11	
12-14		12-15	

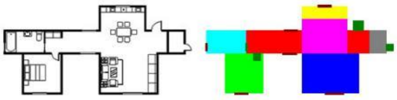
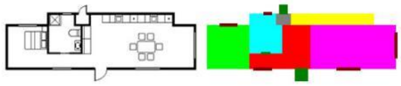
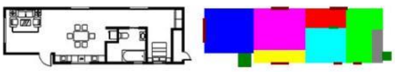
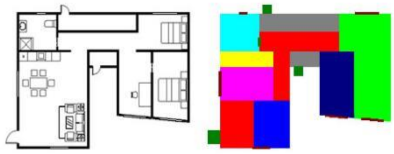
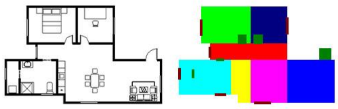
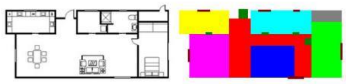
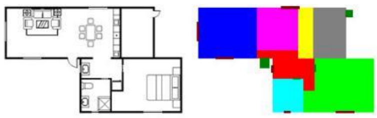
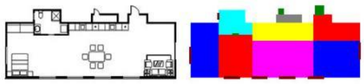
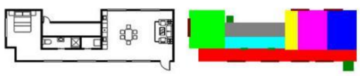
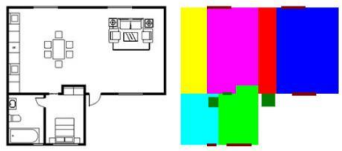
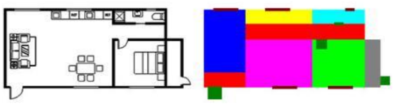
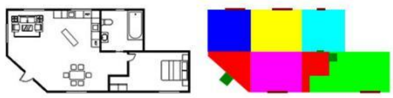
No.	Sample	No.	Sample
12-16		13-01	
13-02		13-03	
13-05		13-06	
13-07		13-08	
13-11		13-12	
13-14		13-15	
13-16		13-17	

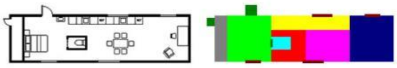
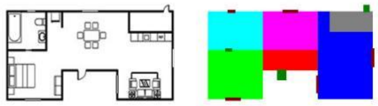
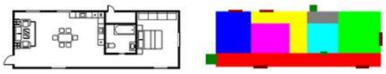
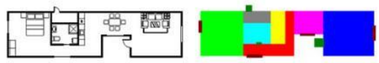
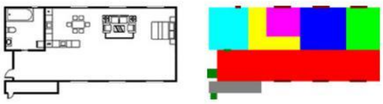
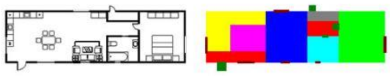
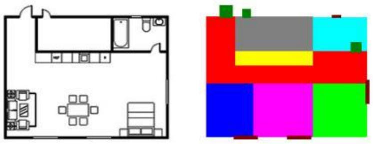
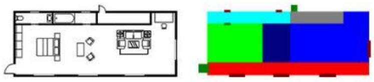
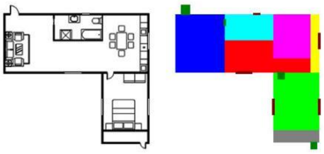
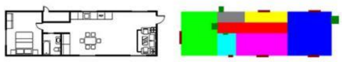
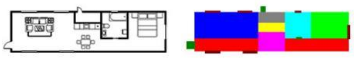
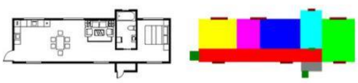
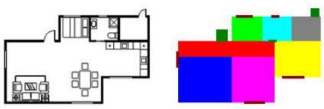
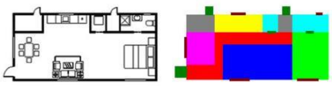
No.	Sample	No.	Sample
13-18		13-19	
13-20		15-1	
15-03		15-06	
15-07		15-08	
15-10		15-11	
15-12		15-13	
15-14		15-15	

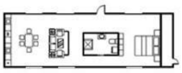
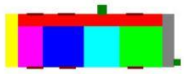
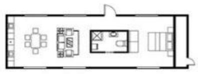
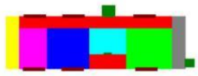
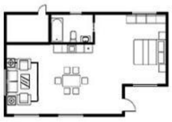
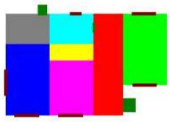
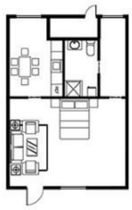
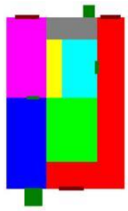
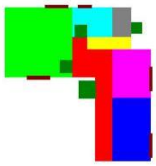
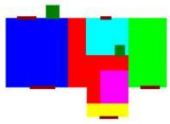
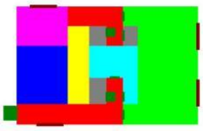
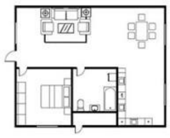
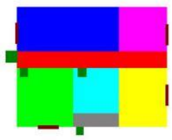
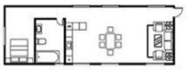
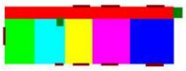
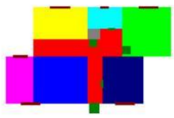
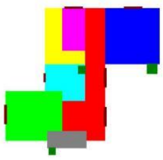
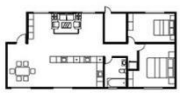
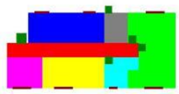
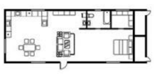
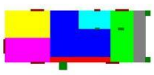
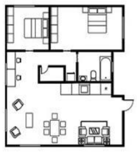
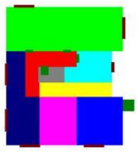
No.	Sample	No.	Sample
17-02		17-04	
17-05		17-06	
17-07		17-08	
17-09		17-10	
17-11		18-01	
18-03		18-05	
18-07		18-08	

No.	Sample	No.	Sample
18-09		18-14	

Appendix B - SD-GAN Raw Dataset II

No.	Sample	No.	Sample
07-01		07-03	
07-04		07-05	
07-06		07-07	
07-09		07-13	
07-14		07-15	
07-18		07-19	

No.	Sample	No.	Sample
07-20		09-02	
09-03		09-04	
09-06		09-09	
09-10		09-13	
09-14		09-15	
09-16		09-17	
09-18		09-19	

No.	Sample	No.	Sample
09-20	 	10-01	 
10-02	 	10-04	 
10-11	 	10-13	 
11-1	 	11-03	 
11-04	 	11-05	 
11-06	 	11-07	 
11-09	 	11-10	 

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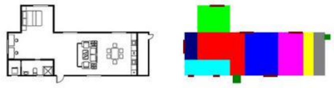
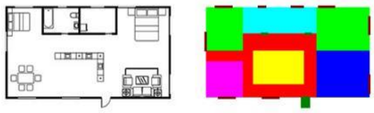
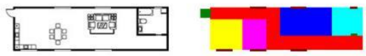
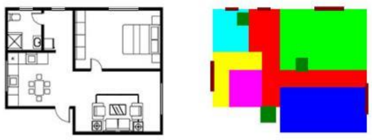
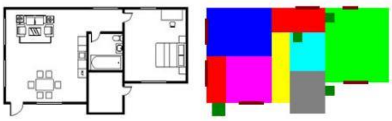
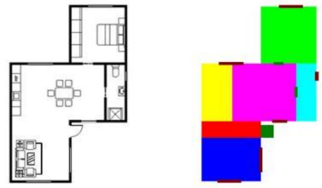
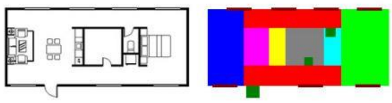
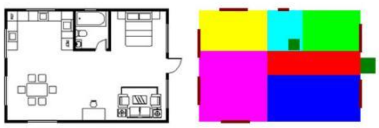
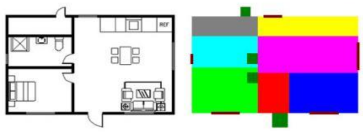
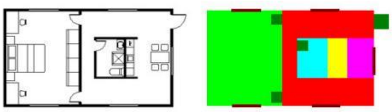
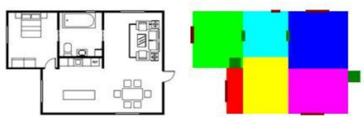
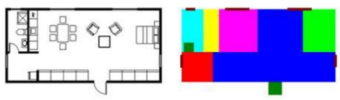
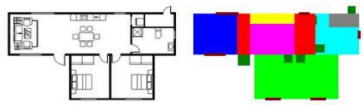
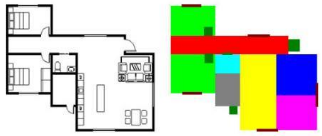
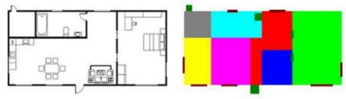
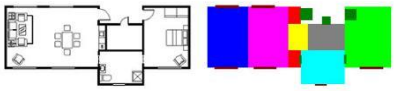
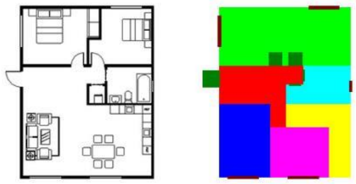
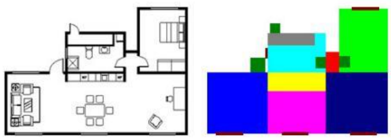
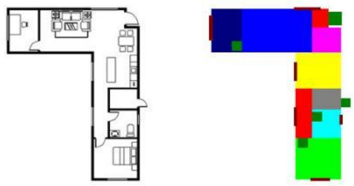
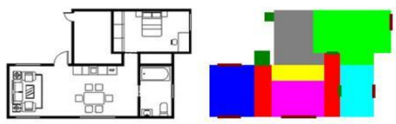
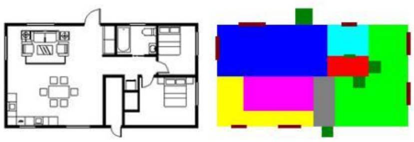
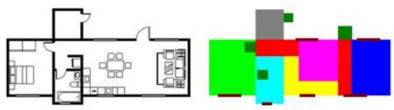
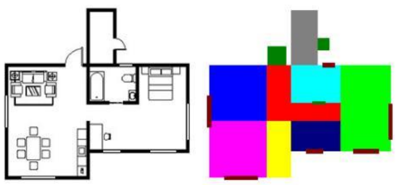
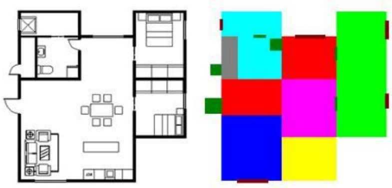
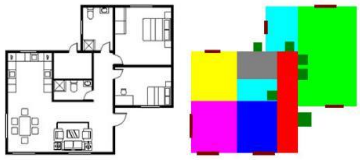
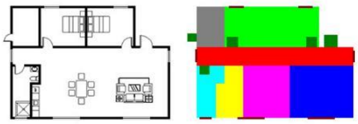
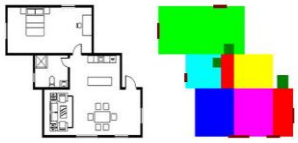
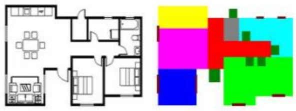
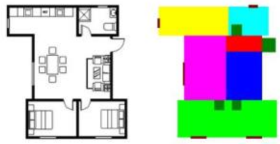
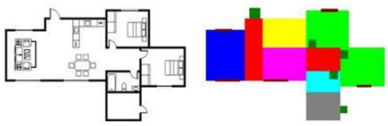
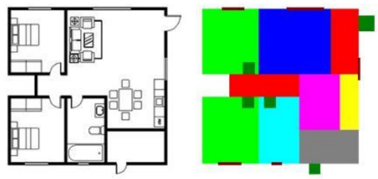
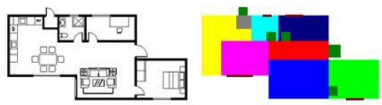
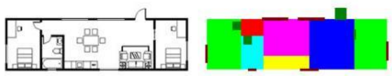
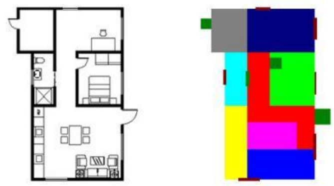
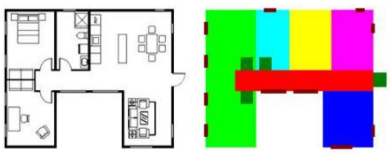
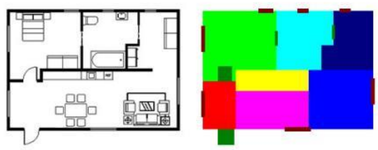
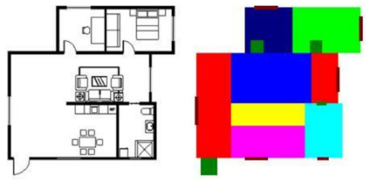
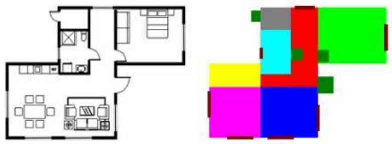
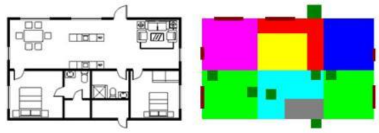
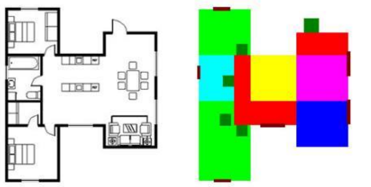
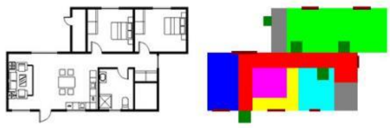
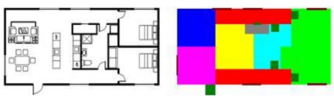
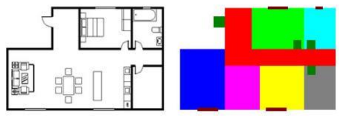
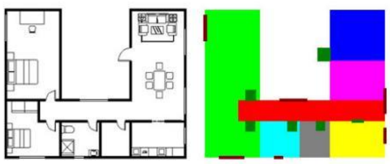
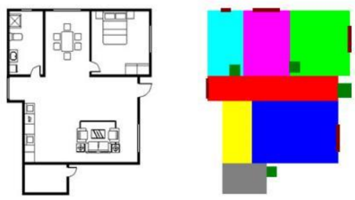
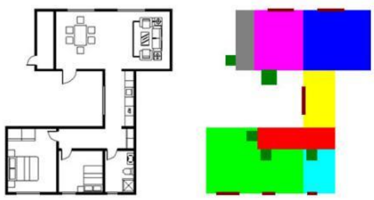
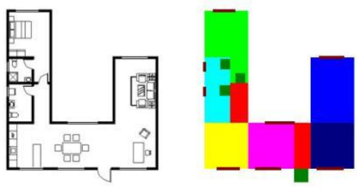
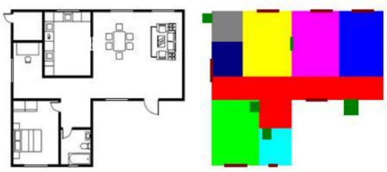
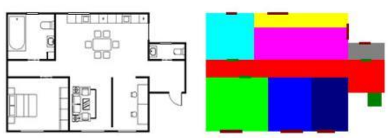
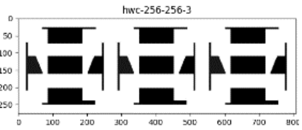
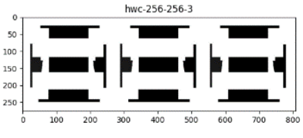
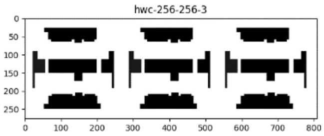
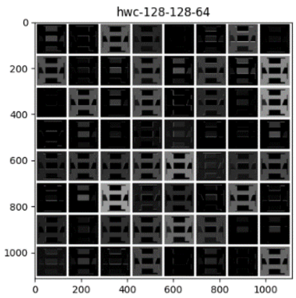
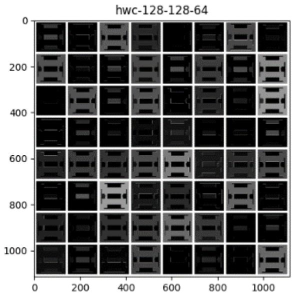
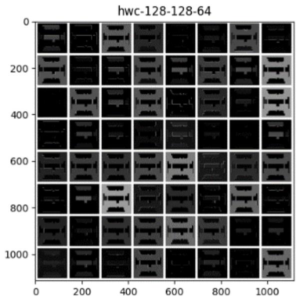
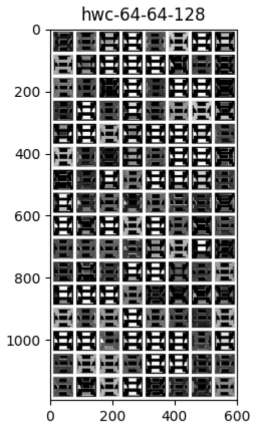
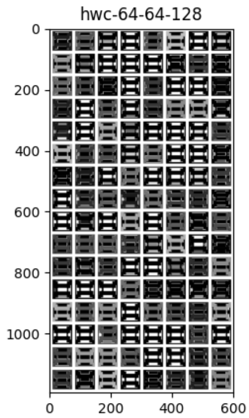
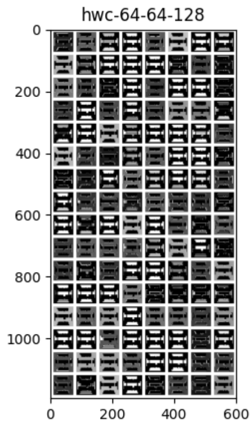
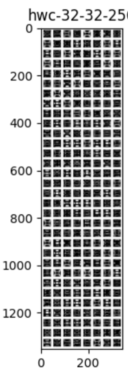
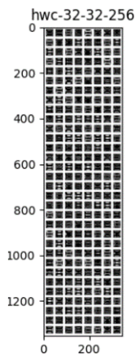
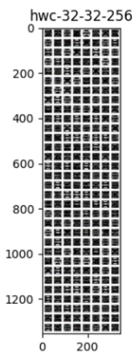
11-12		11-15	
11-16		11-18	
11-19		12-01	
12-03		12-04	
12-09		12-11	
12-14		12-15	
12-16		13-1	

No.	Sample	No.	Sample
13-02		13-03	
13-05		13-06	
13-07		13-08	
13-11		13-12	
13-14		13-15	
13-16		13-17	
13-18		13-19	

No.	Sample	No.	Sample
13-20		15-01	
15-03		15-06	
15-07		15-08	
15-10		15-11	
15-12		15-13	
15-14		15-15	
17-02		17-04	

No.	Sample	No.	Sample
17-05		17-06	
17-07		17-08	
17-09		17-10	
17-11		18-01	
18-03		18-05	
18-07		18-08	
18-09		18-14	

Appendix C - Visualization of U-net Training

Layer	Case A	Case B	Case C
Down 1			
Down 2			
Down 3			
Down 4			

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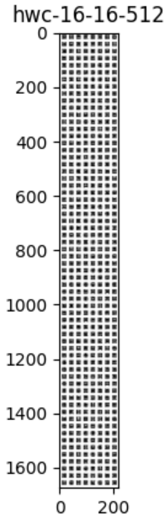
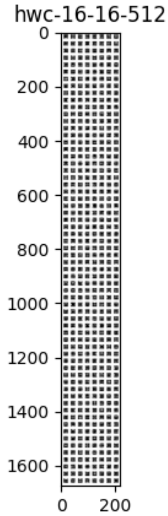
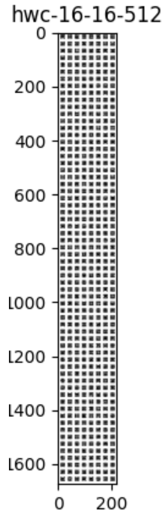
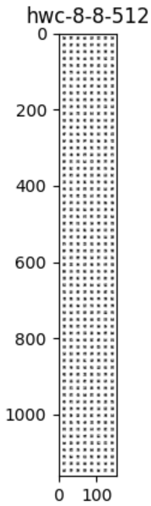
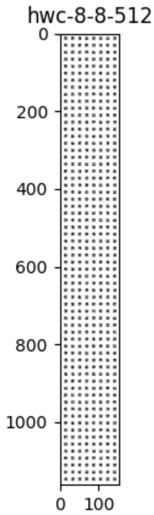
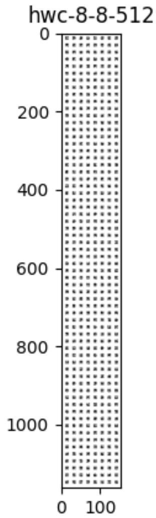
<tr><td>Down 5</td><td></td><td></td><td></td></tr>
<tr><td>Down 6</td><td></td><td></td><td></td></tr>
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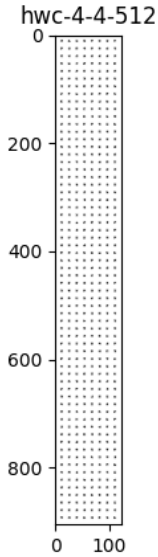
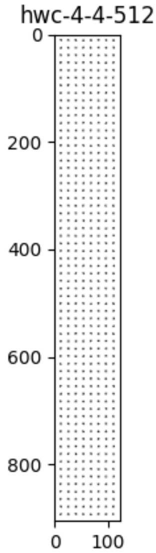
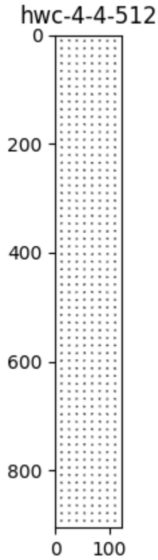
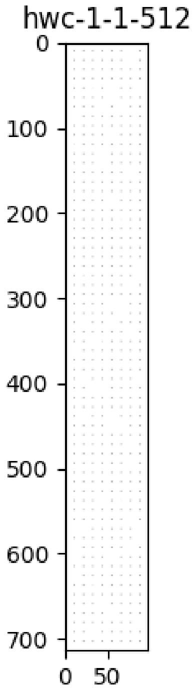
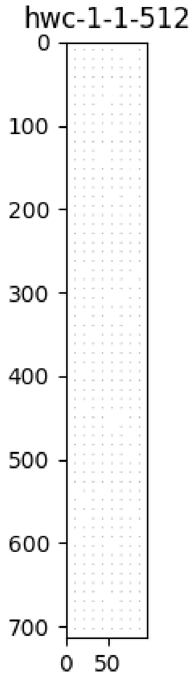
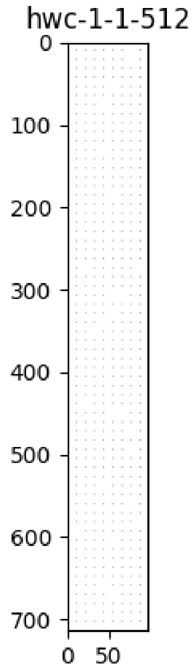
Layer	Case A	Case B	Case C
Down 7			
Up 1			

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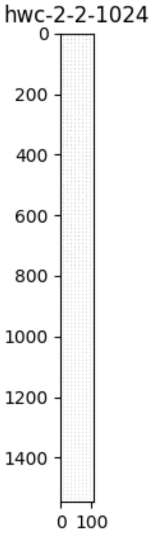
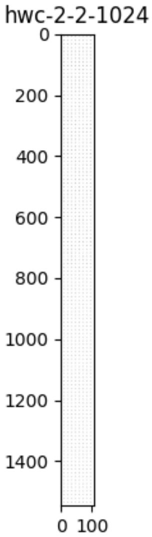
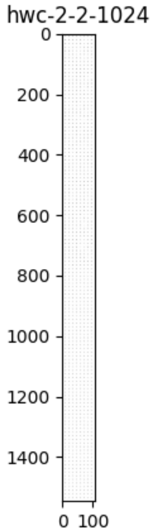
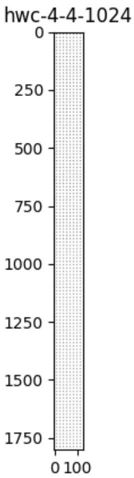
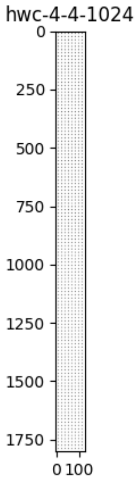
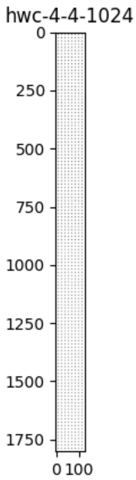
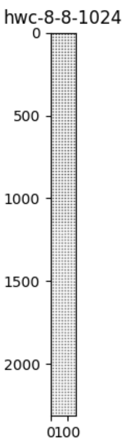
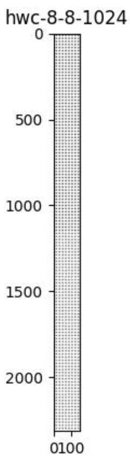
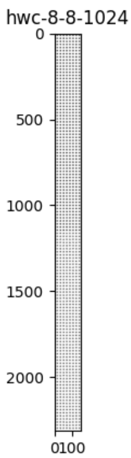
<tr><td>Up 2</td><td></td><td></td><td></td></tr>
<tr><td>Up 3</td><td></td><td></td><td></td></tr>
<tr><td>Up 4</td><td></td><td></td><td></td></tr>
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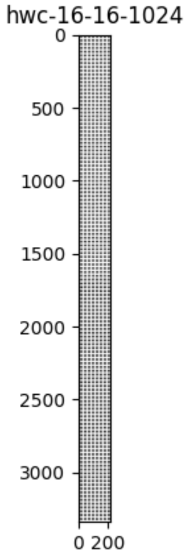
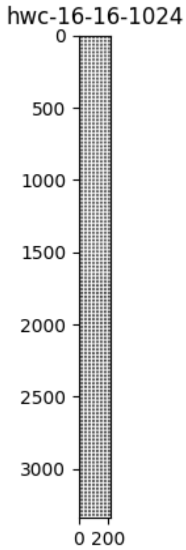
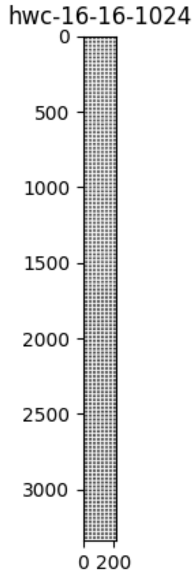
<tr><th>Layer</th><th>Case A</th><th>Case B</th><th>Case C</th></tr>
<tr><td>Up 5</td><td>
</td><td>
</td><td>
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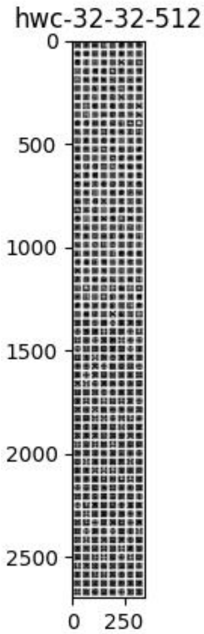
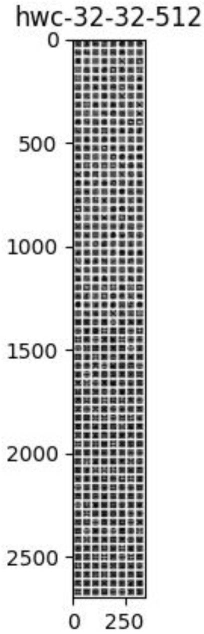
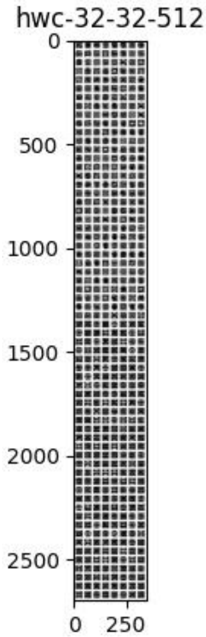
<tr><td>Up 6</td><td>
</td><td>
</td><td>
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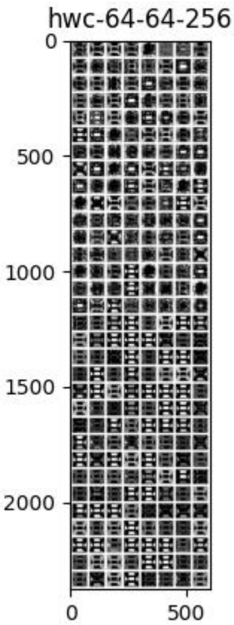
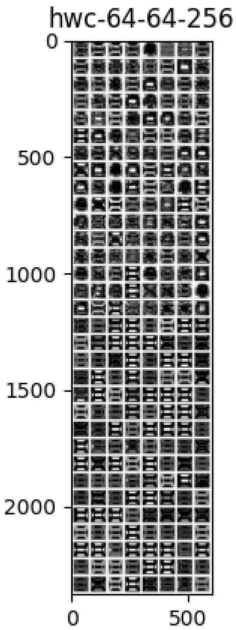
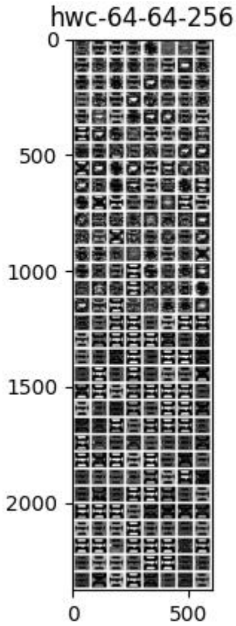
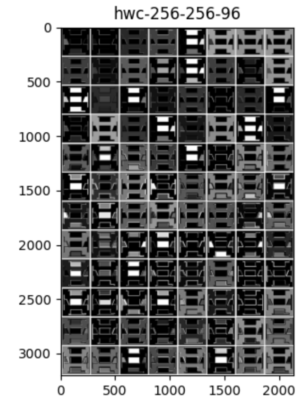
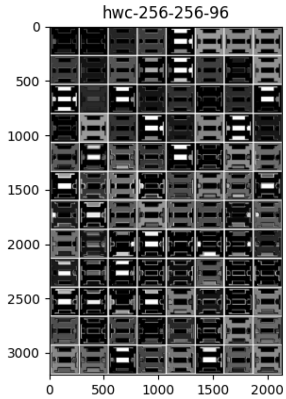
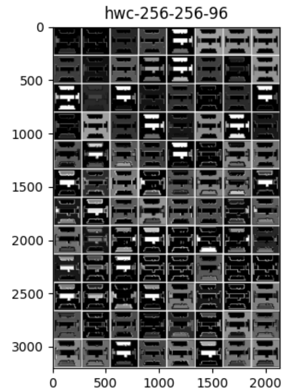
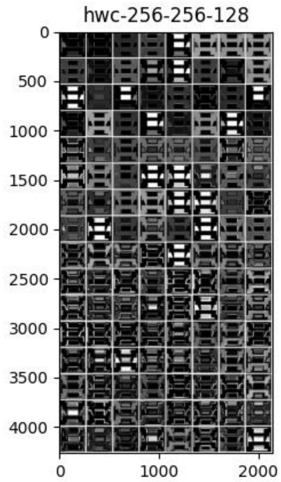
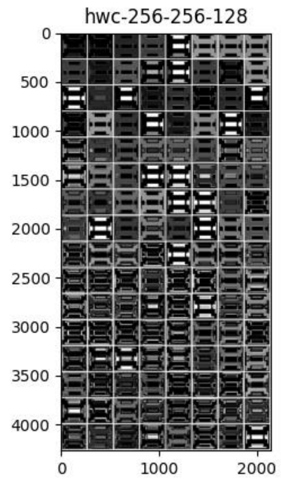
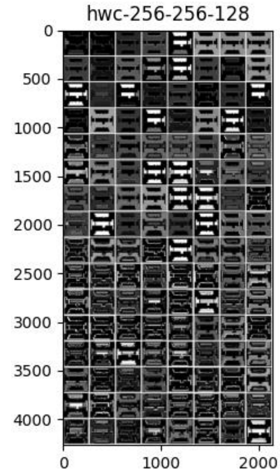
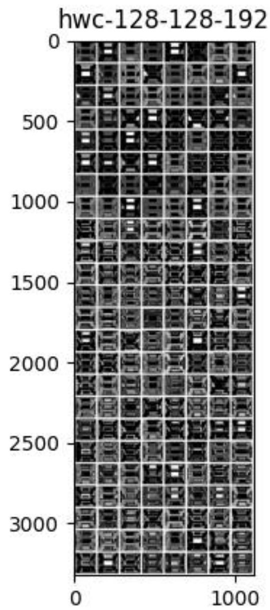
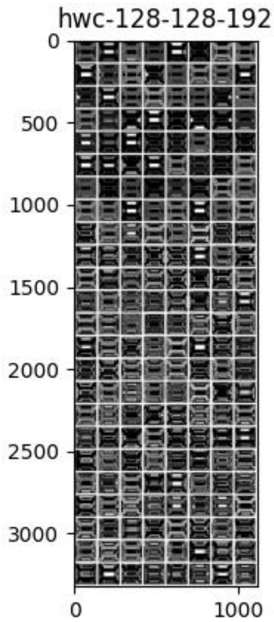
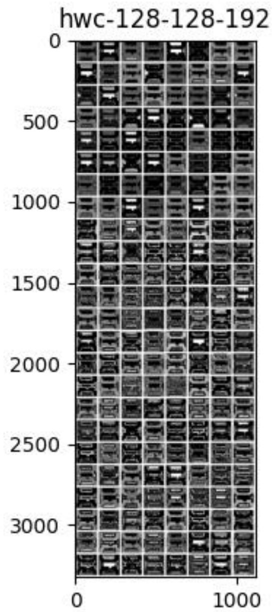
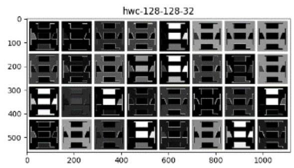
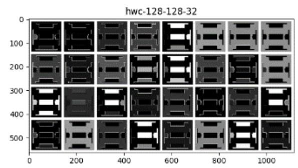
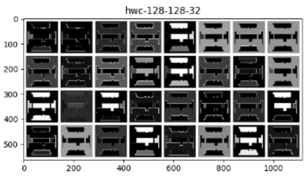
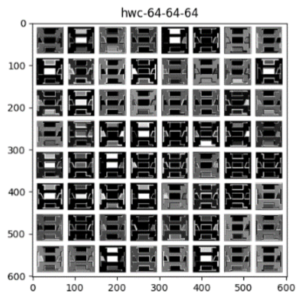
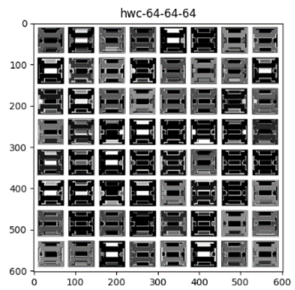
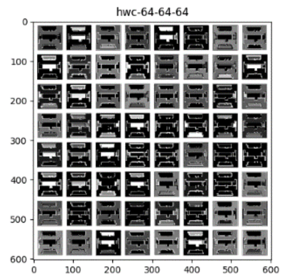
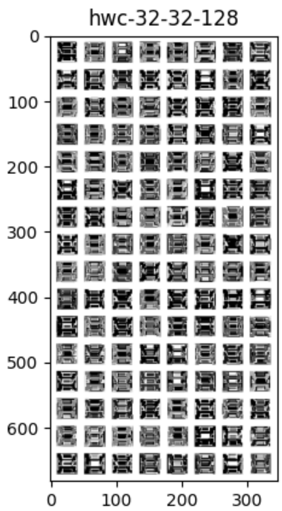
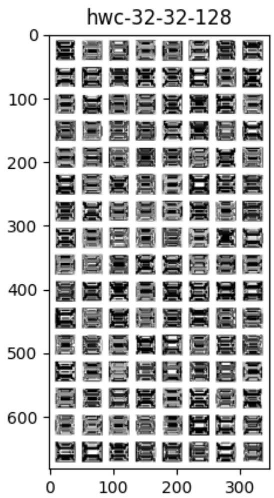
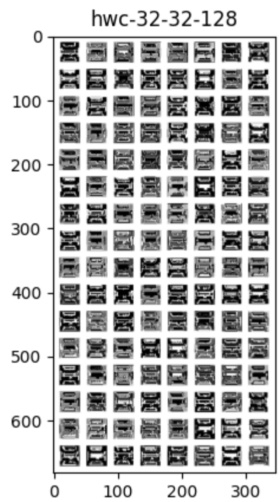
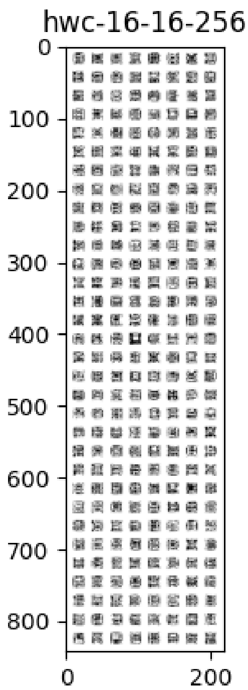
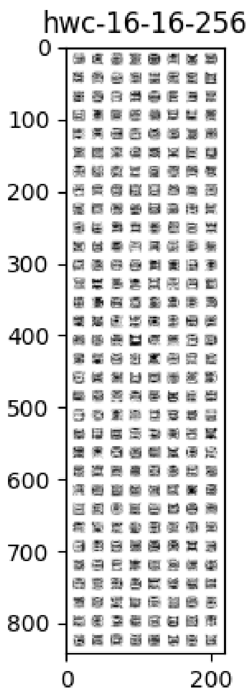
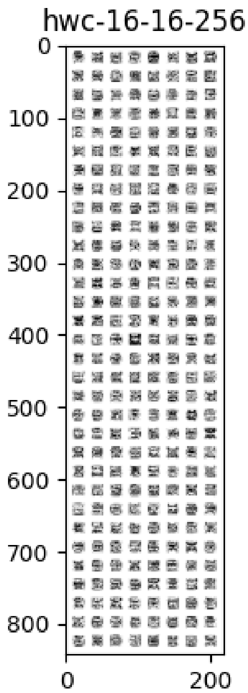
Layer	Case A	Case B	Case C
Up 7			

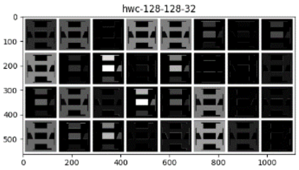
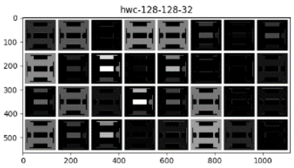
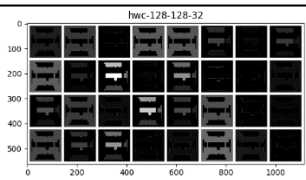
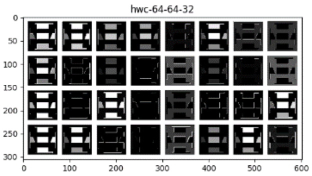
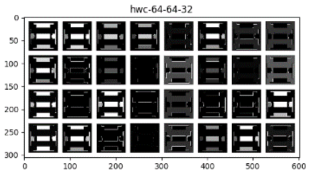
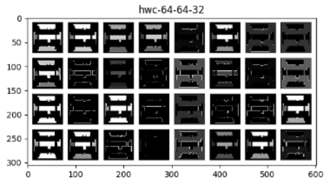
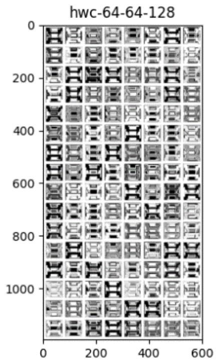
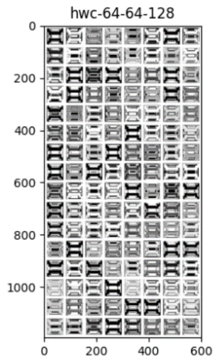
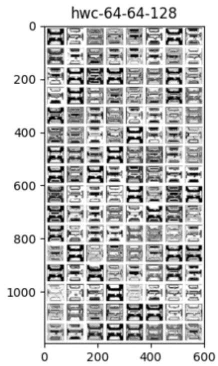
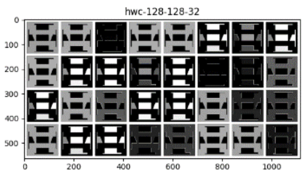
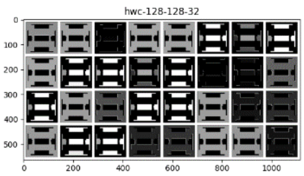
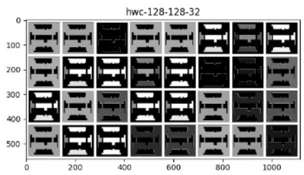
Appendix D - Visualization of U-net++ Training

Layer	Case A	Case B	Case C
Conv 0-1			
Conv 0-2			

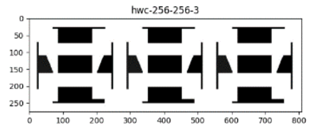
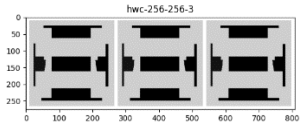
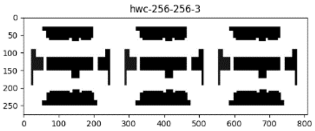
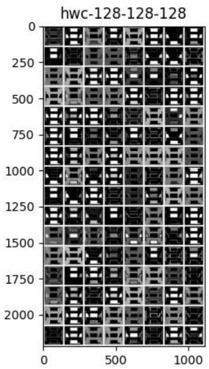
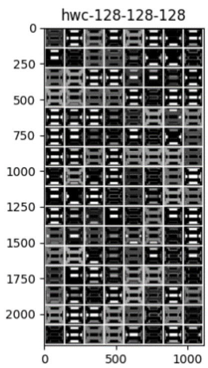
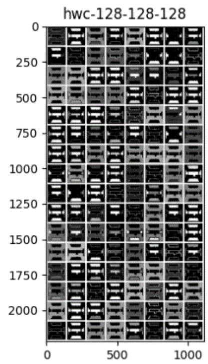
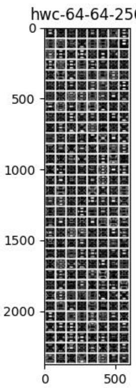
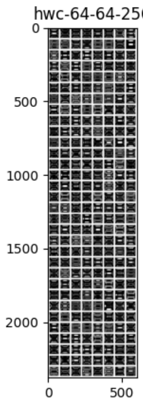
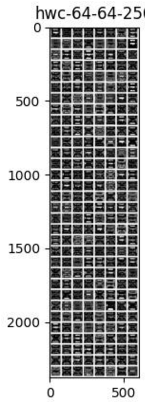
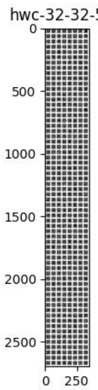
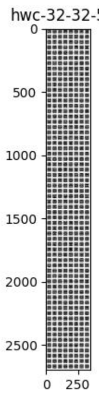
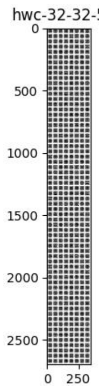
Layer	Case A	Case B	Case C
Conv1-1			
Conv1-2			
Conv2-0			

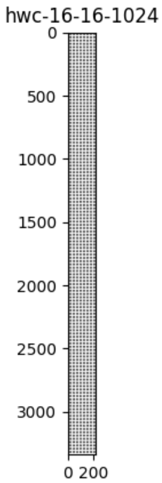
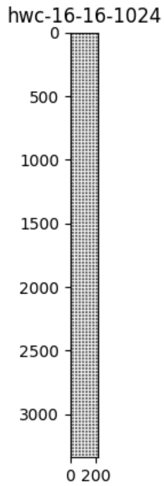
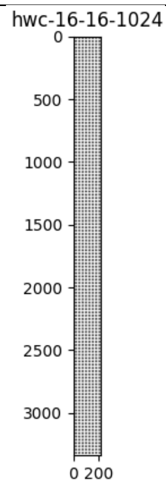
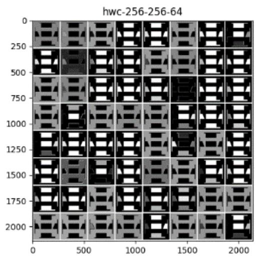
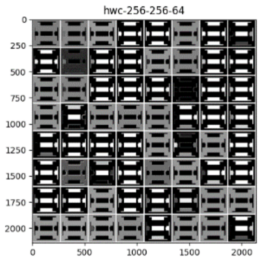
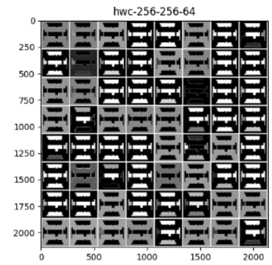
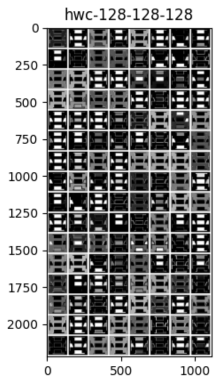
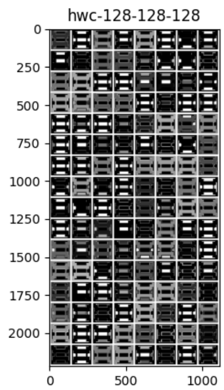
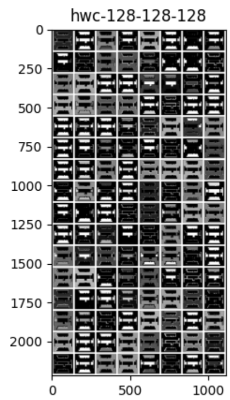
Layer	Case A	Case B	Case C
Conv 3-0			
Conv 4-0			

Appendix E - Visualization of HRNet Training

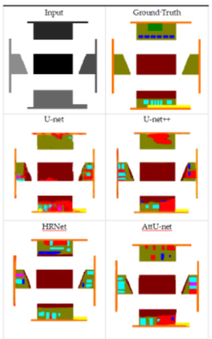
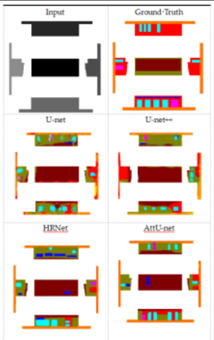
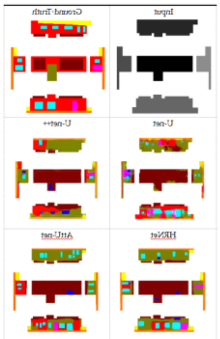
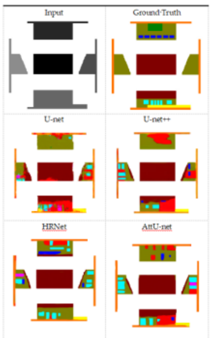
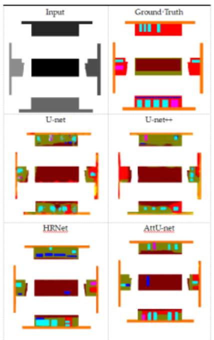
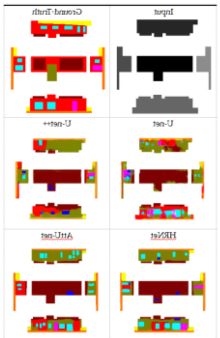
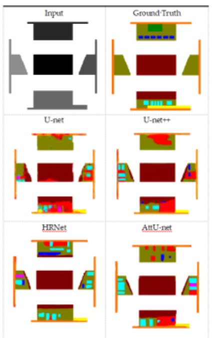
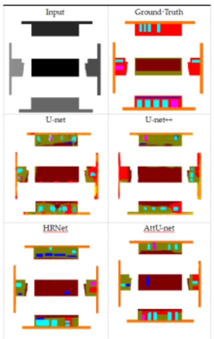
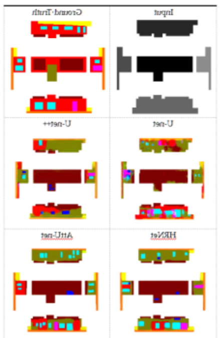
Layer	Case A	Case B	Case C
Conv1			
Conv2			
Layer1			
Relu			

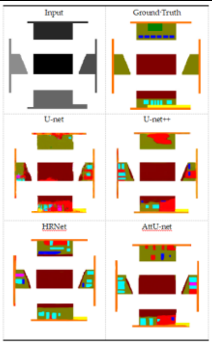
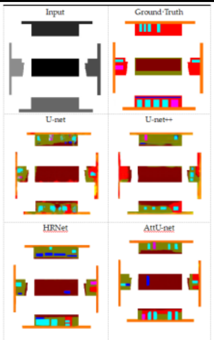
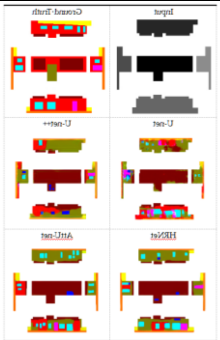
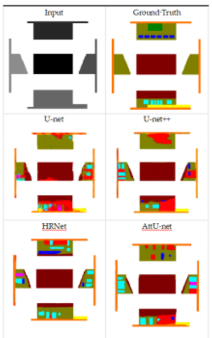
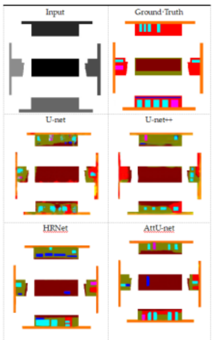
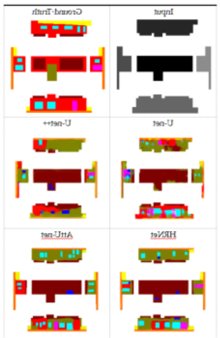
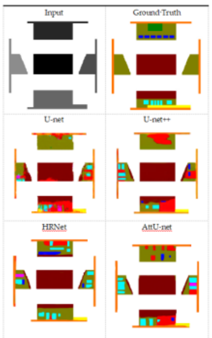
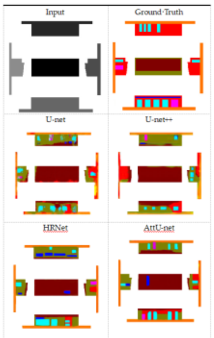
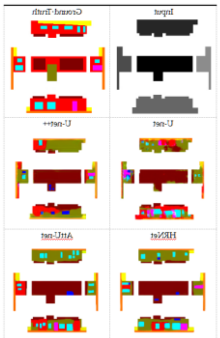
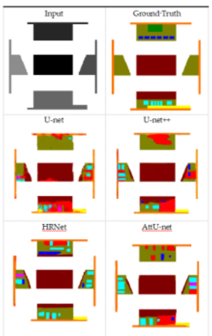
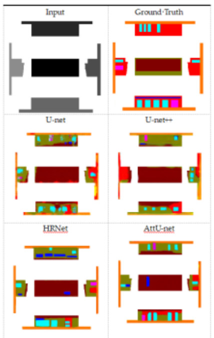
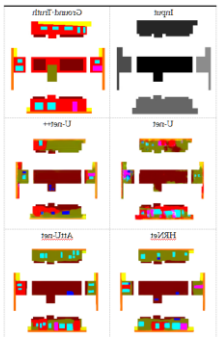
Appendix F - Visualization of AttU-net Training

Layer	Case A	Case B	Case C
Conv 1			
Conv 2			
Conv 3			
Conv 4			

Layer	Case A	Case B	Case C
Conv 5			
Maxpooling 1			
Maxpooling 2			

Appendix G - Questionnaire on Simulation Results of Different Generators

Question	Case A	Case B	Case C	Score
Generate Images with Clear Borders				
Image Quality Without Aliasing				
The Color Block Generated in A Reasonable Position				

Question	Case A	Case B	Case C	Score
Unity Of the Whole and The Part				
Harmony Of Proportion and Scale				
Energy Efficiency Performanc e				
Design Performanc e				

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