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EXPLORING DEEP GENERATIVE MODELS IN BUILDING DESIGN

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Abstract

The complex and time-consuming nature of building design necessitates meticulous attention to detail and adherence to principles. Automation in the design process is crucial with a growing demand for innovative and sustainable structures. This review explores the transformative impact of integrating deep generative models into building design, showcasing their ability to generate realistic 3D models, layouts, and structural designs. These models address challenges in architectural design and sustainability assessment, enabling generative design and energy-efficient building design. The review suggests potential solutions and highlights the role of the models in enhancing sustainability, cost-efficiency, and creativity in the built environment.

Keywords: Design automation, Deep generative models, Generative adversarial networks, Variational autoencoders, Reinforcement learning

Introduction

The building industry faces a critical challenge in enhancing the efficiency, cost-effectiveness, and sustainability of design processes in the built environment. There is an urgent need for research and development focused on integrating automation into design processes to address this challenge (Bourahla et al., 2022; Rigger et al., 2018). The paramount importance of streamlining design procedures, reducing time and costs, and increasing productivity necessitates a thorough investigation of traditional design methodologies.

The potential for the building industry to significantly decrease design timelines and environmental impact underscores the urgency of addressing this issue. In this context, design automation emerges as a promising solution, utilizing computer capabilities to quickly produce diverse design options that meet complex objectives. Therefore, designers can evolve and refine designs efficiently, minimizing material consumption and enhancing efficiency (Jiang et al., 2023; Karan and Asadi, 2019; Lagaros and Papadrakakis, 2012; Zhang and Mueller, 2017).

Recent advancements in artificial intelligence (AI) and intelligent optimization algorithms have led to the development of new generative design (GD) algorithms and systems. Intelligent optimization, with its ability to find optimal solutions that maximize or minimize specific objective functions, is ideal for structural design purposes (Pan and Zhang, 2021). The integration of AI techniques in the building industry has been steadily growing (Kookalani et al., 2022a, 2022b, 2021; Kookalani and Cheng, 2022, 2021a, 2021b), with the adoption of GD methodologies and AI-driven optimization techniques poised to transform how structures are designed, constructed, and operated. Deep generative models (DGMs) significantly impact GD by streamlining processes, reducing errors, and enhancing design possibilities.

This paper aims to extensively examine DGMs and their role in optimizing structures. The study highlights DGM applications in the building design industry, emphasizing their ability for intelligent optimization. Complex algorithms enable architects and engineers to efficiently explore design alternatives, providing opportunities for real-time feedback. This allows designers to make informed decisions and create structures that are not only aesthetically appealing but also functionally efficient and sustainable.

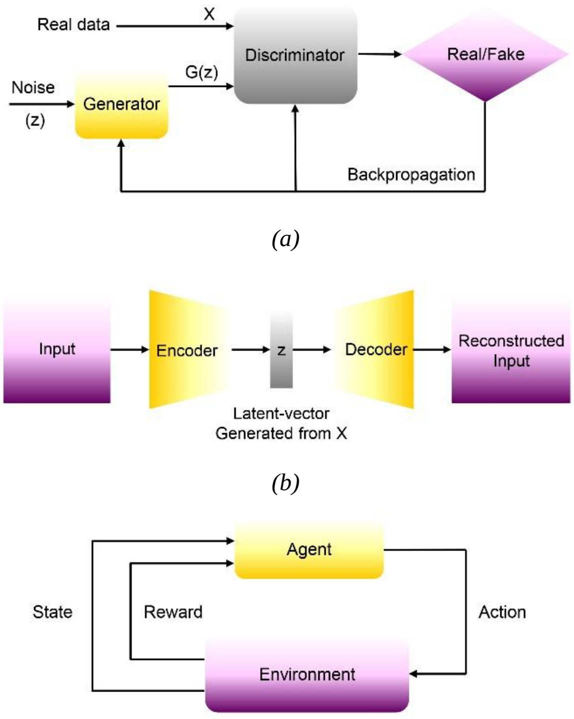
Methodology

This section outlines the methodology employed in conducting the literature review for this paper, which delves into the application of DGMs in the field of building design. Specifically, the focus lies on exploring DGMs, which encompass GANs, VAEs, and RL techniques. A systematic search was conducted within the Web of Science Core Collection database to identify relevant scholarly papers. The search query employed the keywords ("deep generative models") AND ("architecture" OR "building" OR "structural engineering") AND ("generative adversarial network" OR "variational autoencoder" OR "reinforcement learning"). The search was constrained to categories related to architecture and civil engineering, yielding 34 initial papers. Additionally, supplementation from the references of these papers led to the inclusion of 55 relevant papers for review.

Deep Generative Models (DGMs)

GD supported by AI techniques has emerged as a transformative force in reshaping the landscape of architectural and engineering practices. This synthesis of GD principles with the power of AI, particularly DGMs, holds great promise for optimizing structures and steering the construction industry towards a more sustainable future.

DGMs, encompassing models like generative adversarial networks (GANs), variational autoencoders (VAEs), and reinforcement learning (RL), play a pivotal role in the automation of GD and analysis processes. Diagrams of these methods are presented in Figure 1. They utilize the capabilities of AI algorithms to facilitate the exploration of complex design spaces, generating efficient and aesthetically pleasing solutions. Notably, DGMs streamline the analysis and design of structural members, eliminating the need for extensive manual iterations by structural engineers.



(a)

(b)

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Figure 1. DGMs: (a) GAN; (b) VAE; (c) RL.

The integration of grid search accessible hyperparameters enhances the effectiveness of deep learning (DL) models. This integration enables engineers to anticipate and determine optimal performance levels with greater accuracy and efficiency, contributing to the advancement of automated GD and analysis (Torky and Aburawwash, 2018).

Several studies exemplify the application of DGMs in the field of automated GD and analysis. Yoo et al. (Yoo et al., 2021) propose a DL-driven computer-aided engineering system for conceptual design, demonstrating enhanced efficiency in structural engineering. Steuben et al. (Steuben et al., 2016) focus on AI-driven optimization of geometry partitioning for 3D printing, showcasing the potential for efficient prefabrication. Li et al. (Li et al., 2023) introduce a process for optimizing clash-free rebar design through the combination of graph neural networks (GNN) and exploratory genetic algorithms (GA).

DGMs, such as GANs, VAEs, and RL, empower architects to streamline their workflow and explore innovative design possibilities efficiently. These models find applications in indoor scene synthesis, conceptual designs, floor plan generation, architectural style identification, and architectural drawing recognition. Notable advancements include single-image 3D reconstruction (Girdhar, 2016) and the utilization of denoising autoencoders for completing 3D shapes (Sharma et al., 2016). Higharc ("Higharc – The intelligent homebuilding platform.," n.d.), a company employing AI, utilizes DGMs for diverse architectural plans, utilizing tools like Finch ("Finch – Optimizing Architecture," n.d.) that integrate Machine Learning (ML) and DL for conceptual designs and plan generation within the architecture field.

In summary, GANs, VAEs, and RL have improved automated GD and analysis in the building industry. GANs focus on data generation, VAEs on data compression and generation, and RL on training agents for sequential decision-making. These models offer opportunities to enhance structural analysis, optimize geometry and material distribution, and foster innovative architectural designs. The integration of DGMs into building design processes holds significant potential for advancing sustainable and visually appealing structures, aligning with global efforts to address environmental concerns, particularly in the context of smart cities and carbon emission mitigation. The continued evolution of DGMs promises to shape a future where AI-driven GD is a fundamental element of architectural, engineering, and construction practices.

Generative adversarial networks (GANs)

GANs have emerged as a powerful DL algorithm with widespread applications in generative modeling across diverse domains, encompassing image, video, and audio generation. Wu et al. (Wu et al., 2022) conducted a comprehensive review, elucidating the diverse applications of GANs in addressing complex challenges within the built environment. However, they highlighted a shared obstacle within this domain, namely the scarcity of meticulously curated datasets tailored for issues encountered in the built environment.

The GAN architecture fundamentally comprises two pivotal components: the generator and the discriminator. The generator is tasked with crafting new data instances replicating the training dataset, guided by feedback from the discriminator. On the other hand, the discriminator plays a crucial role in distinguishing real data from the training set and data synthesized by the generator. This adversarial interplay contributes to the overall learning process of GANs, with the discriminator offering critical feedback on the quality of the generated output.

In the realm of architecture, GANs have catalyzed a significant transformation, automating the generation and design of diverse architectural elements. This includes facades, interior layouts, building masses, and floor plans (Chaillou, 2020)**.** Notable examples such as ArchiGAN, House-GAN, and House-GAN++ showcase the expertise of GANs in generating fully furnished architectural plans and automated house layouts (Chaillou, 2019)**,** (Nauata et al., 2021, 2020)**,** Architectural constraints are utilized, allowing architects to transform generated layouts into physical floor plans, exemplifying the practical applications of GANs in architectural design, as shown in Figure 2.

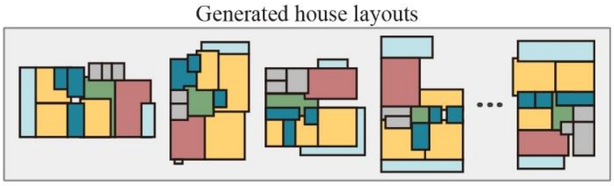

Figure 2. Automatically generating multiple house layout options by House-GAN (Nauata et al., 2020).

Subsequently, Nauata et al. (Nauata et al., 2020) illustrated a comprehensive analysis of failure and success instances, aligned with the ground-truth data, in their user study, as depicted in Figure 3. The first failure example appears unusual as a balcony is only accessible through bathrooms, and a closet is situated within a kitchen, while the second failure example seems odd due to a kitchen being divided into two disconnected spaces.

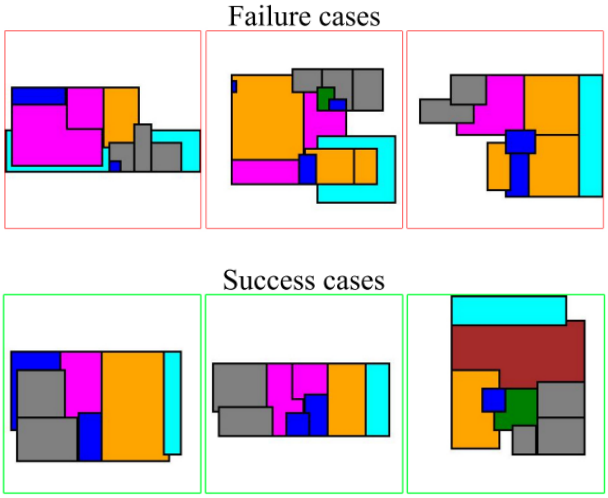

Figure 3. Failure and success examples by House-GAN from the user study (Nauata et al., 2020).

Expanding beyond conventional design realms, GANs have been employed in intelligent shear wall structure design (Zhao et al., 2023) and autonomous architectural sketch design (Qian et al., 2023, 2022)**.** The versatility of GANs is further evidenced by their application in automating the design of shear walls, beams, and slabs in a two-dimensional plane (Liao et al., 2021; Lu et al., 2022; Zhao et al., 2022)**.** Innovative approaches such as TxtImg2Img (Liao et al., 2022), modal expansion of reticulated shells (Zhang et al., 2023), and modular building plan creation (Ghannad et al., 2021) underscore potential of GANs to transform structural design processes, offering practical solutions in the building and construction industry.

In summary, the landscape of GANs in building and structural design is dynamic and expansive. Open-source repositories, including pix2pix (Isola et al., 2016), SEASAME (Park et al., 2019), CycleGAN (Zhu et al., 2017), StyleGAN (Karras et al., 2019), AttnGAN (Xu et al., 2017), and GraphGAN (Wang et al., 2017), further exemplify versatility of GANs in addressing specific challenges across various fields, including construction and building industry. The continued evolution of GANs and their innovative applications underscore their potential to reshape and streamline complex design processes, fostering efficiency and innovation in the built environment.

Variational autoencoders (VAEs)

VAEs have emerged as a prominent class of DGMs, garnering significant attention across various ML domains (Czerniawski et al., 2021; Weng et al., 2023)**.** Their success, demonstrated since their introduction in 2013, stems from their ability to address limitations faced by traditional autoencoders, particularly in sampling realistic latent vectors due to the sparsity of real data distribution in the latent space.

A fundamental characteristic of VAEs is their integration of regularization techniques to mold a well-organized latent space during training. VAEs introduce a probabilistic sampling approach in the latent space unlike conventional autoencoders, as proposed by Kingma and Welling (Kingma and Welling, 2013)**.** The encoder of a VAE produces mean and variance values, enabling the sampling of latent vectors before decoding. The incorporation of a Kullback–Leibler divergence loss ensures a predictable latent space distribution, addressing the sparsity issue encountered by traditional autoencoders.

In the realm of deep neural networks (DNNs), VAEs have found particular utility in generative architectural designs, specifically in 2D and 3D applications. The regularization techniques employed by VAEs facilitate the creation of well-structured latent spaces, enhancing the generative process. This capability has been exemplified in the work of Wu et al. (Wu et al., 2019)**,** who introduced an encoder-decoder network algorithm for generating floor plans, effectively enforcing room location constraints. Furthermore, Mirra and Pugnale (Mirra and Pugnale, 2021) utilized VAEs to generate topological variations of shell structure forms, highlighting the adaptability of VAEs in diverse design spaces. In addition, Danhaive and

Mueller (Danhaive and Mueller, 2021) developed a methodology using conditional variational autoencoders within a performance-guided design exploration framework to construct advanced latent variable models, enabling the representation of intricate design spaces in lower-dimensional subspaces optimized for performance-driven outcomes, as shown in Figure 4. This study demonstrates that design subspace learning offers a promising solution to overcome inherent limitations in current computational design methods, providing a more intuitive and effective interface for human designers to navigate complex design spaces, thus facilitating the broader adoption of performance-informed design processes.

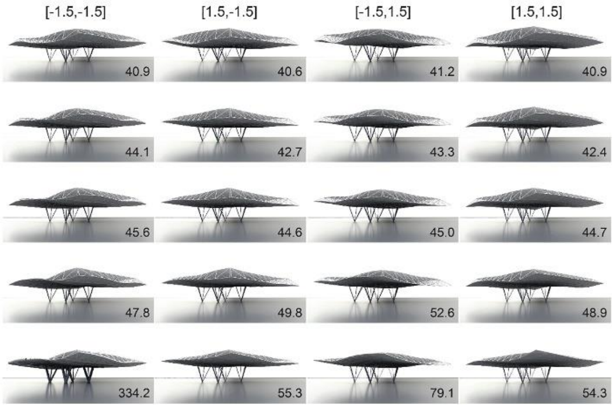

Figure 4. Morphological and performance evolution of designs in the latent space (Danhaive and Mueller, 2021).

In the context of unconditional 3D shape synthesis, VAEs exhibit significant potential (Soltani et al., 2017). Notably, they have been successfully applied to create meshes for modeling faces and human bodies, showcasing the versatility of VAEs in specific domains (Tan et al., 2017)**.** The ability to condition VAE training on design constraints or user preferences parallels the approach taken with GANs. However, VAEs possess an inherent advantage with a latent space that already exhibits some degree of structure. Researchers have developed conditional variational autoencoders (CVAEs) to enhance interpretability and control. CVAEs extend conventional VAEs by incorporating a conditioning vector as input to both the encoder and the decoder, facilitating the integration of design constraints and user preferences in the generative process (Danhaive and Mueller, 2021)**.**

In summary, VAEs have proven to be a powerful tool, offering solutions to challenges faced by traditional autoencoders. Their success in various ML applications, coupled with their adaptability to different design domains, underscores their significance in shaping the future of generative modeling.

Reinforcement learning (RL)

RL distinguishes itself from other DGMs by its unique ability to learn in an unsupervised manner, obviating the need for a pre-existing dataset. Instead, RL operates through trial-and-error interactions between an actor and an environment, with the goal of maximizing rewards accrued through decision-making and action-taking (Kaelbling et al., 1996). The central objective of the actor in RL is to optimize the total reward obtained, casting RL as a form of optimization process.

An early fusion of DL and RL was pioneered by Mnih et al. (Mnih et al., 2015), who integrated DL with Q-learning. Q-learning revolves around learning the state-action value function, known as the Q-function, estimating the potential reward associated with a specific action taken in a given state. The introduction of convolutional neural networks (CNNs) in this paradigm enabled the learning of the Q-function.

In the realm of design, RL unfolds as a sequential process, iteratively modifying or generating designs through a series of actions. The quality or performance of the resulting design serves as the reward signal, effectively acting as the environment for RL. While RL eliminates the need for a conventional dataset, it heavily depends on meaningful and reliable reward signals, often necessitating a high-fidelity simulation environment. A key advantage of RL over GANs and VAEs is its flexibility in defining the reward function based on any objective, which need not necessarily be differentiable. In contrast, GANs and VAEs rely on gradient-based optimization and require any added objectives in their loss functions to be differentiable.

In engineering design, RL has been successfully applied to address inverse design problems, seamlessly combining learning with design optimization. Dworschak et al. (Dworschak et al., 2022) proposed a comprehensive approach for design automation using RL for parametric computer-aided design (CAD) models. Cui et al. (Cui et al., 2012) employed Q-learning for design optimization, while Yonekura and Hattori (Yonekura and Hattori, 2019), and Lee et al. (Lee et al., 2019) implemented double deep Q-learning (DQN). Sun and Ma (Sun and Ma, 2020) extended four well-known exploration techniques in RL to generate multiple solutions. Shi et al. (Shi et al., 2020) introduced an innovative algorithm that combines RL with off-policy monte-carlo tree search for generative floor plan design.

Jeong and Jo (Jeong and Jo, 2021) presented a novel RL-based method for automated reinforced concrete (RC) beam design. They utilized the deep deterministic policy gradient, employing CNN function approximators. They demonstrated that the RL agent can successfully create continuous beam members with design quality comparable to optimized designs, all without requiring an iterative process. Additionally, a clearly delineated collection of reward functions is essential for the success of the suggested approach in expanding its application in structural design automation. This entails exploring a broader range of cost reward functions.

Liu et al. (Liu et al., 2020) proposed a novel approach employing Q-learning-based multi-agent RL for clash-free rebar automated designs in practical applications involving reinforced concrete structures. The outcomes of the simulation regarding success rates and average time required for rebar designs in RC members revealed that the suggested framework has the potential to substantially diminish engineering duration (up to a 90% reduction) and prevent spatial conflicts among rebars. Hayashi and Ohsaki (Hayashi and Ohsaki, 2021) introduced a novel approach combining RL and metaheuristics for automated optimal cross-sectional design of planar frame structures. It was demonstrated that the optimal simulation outcome improved after completing 100 and 1000 training sessions, successfully reducing the cross sections while adhering to the constraints. Maghami and Hosseini (Maghami and Hosseini, 2022) innovatively incorporated deep reinforcement learning (DRL) to facilitate the automated reverse engineering of layered phononic crystal beams, as depicted in Figure 5. It was demonstrated that the algorithm successfully generated appropriate geometry. Consequently, the integration of RL into engineering design research offers promising solutions for addressing complex optimization challenges.

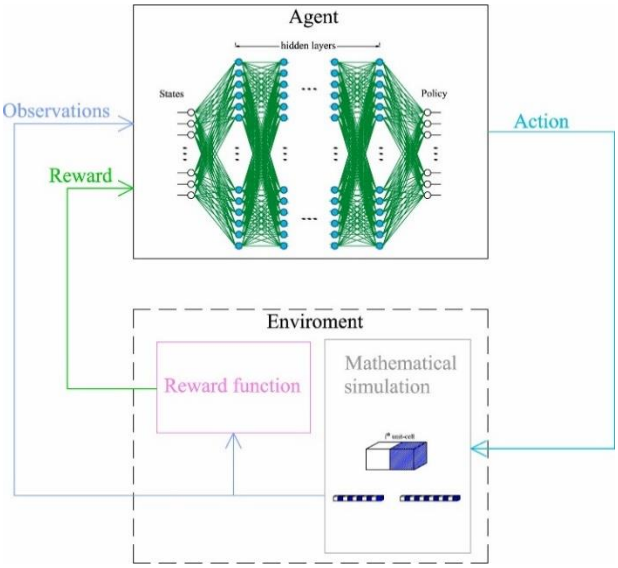

Figure 5. Framework of automated design of layered phononic crystal beams through DRL (Maghami and Hosseini, 2022).

Methods Comparison

GANs, VAEs, and RL are prominent techniques in artificial intelligence, each serving distinct purposes. GANs are primarily geared towards generating realistic synthetic data such as images, audio, and text by learning the data distribution. VAEs, on the other hand, focus on learning latent representations of data, enabling generation, reconstruction, and providing a measure of uncertainty. RL is utilized for sequential decision-making tasks, where an agent interacts with an environment to achieve specific objectives, learning through iterative trial and error processes.

In terms of implementation, GANs consist of two networks: a generator and a discriminator, trained concurrently in a minimax game setup. The generator fabricates samples while the discriminator evaluates their authenticity. VAEs comprise an encoder and a decoder, where the encoder maps input data to a latent space and the decoder reconstructs the input from sampled points. RL involves an agent interacting with an environment to learn a policy maximizing cumulative rewards through exploration and exploitation techniques such as Q-learning and policy gradients.

Applied scenarios highlight the diverse applications of each technique. GANs find utility in generating realistic images for data augmentation, style transfer, and image-to-image translation. VAEs are applied in tasks like image denoising, semi-supervised learning, and generating novel data samples. RL is widely used in robotics, game playing, recommendation systems, autonomous vehicles, design automation, and natural language processing tasks. However, each technique also faces design challenges; GANs may suffer from mode collapse and training instability, VAEs often produce blurry samples, and RL is susceptible to issues like high sample complexity and reward sparsity. Overall, the choice among GANs, VAEs, and RL depends on the specific requirements and constraints of the problem being addressed.

Challenges, Opportunities, and future work

DGMs have emerged as a transformative paradigm in the building and construction fields, offering efficient and user-friendly alternatives to traditional experience-based processes. The exploration of DGMs applications, methodologies, and optimization potential has highlighted a set of challenges and opportunities crucial for its widespread implementation and impact.

The effectiveness of DGMs heavily relies on high-quality and relevant data, posing challenges due to fragmentation, inconsistency, and proprietary nature. Addressing this necessitates efforts in establishing data standards, promoting collaboration, and developing robust data acquisition and preprocessing techniques. Utilizing sensor technology, building information modeling (BIM), and data analytics can enhance data sets, empowering GDM models to generate innovative and optimized solutions tailored to specific project requirements.

Incorporating performance evaluation is crucial for practical DGMs application. Challenges in fidelity, cost, and differentiability need attention. Balancing accuracy and computational cost are essential, and advancements in surrogate models, self-supervised data augmentation, and multi-fidelity modeling show promise in addressing these challenges. Future developments aim to create faster and more accurate evaluation methods.

DGMs involve complex algorithms and optimization processes demanding significant computational resources. Overcoming this complexity requires efficient algorithms, parallel computing techniques, and optimization strategies. High-performance computing architectures, such as tensor processing units and graphics processing units, have accelerated DGM workflows, making tools more accessible. Future advancements, like quantum computing, hold potential for even more sophisticated DGM techniques. Quantum computing holds promise for improving various fields, due to its ability to process vast amounts of data and perform complex calculations at speeds far beyond classical computers. It could potentially enhance DGM techniques by offering more efficient algorithms for data generation. This could lead to the creation of more realistic and higher-quality synthetic data, benefiting applications ranging from data augmentation to simulating complex real-world scenarios.

Current DGMs tend to imitate existing data, impeding the generation of creative or novel designs. Improvements can be achieved by enhancing models like creativeGAN and introducing new features into typical designs. Creative adversarial networks (CAN) can encourage the production of surprising and novel design elements, fostering more human-like creativity in GD.

As DGMs become more complex, the need for interpretability grows. Explainable AI techniques, visualization tools, and interactive interfaces are being developed to explain black-box models. Ensuring interpretability in DGMs enhances collaboration, decision-making, and the adoption of optimized designs.

The potential of DGMs lies in solving complex problems, necessitating collaborations between data scientists, AI experts, and construction professionals. Interdisciplinary collaborations ensure a deep understanding of domain-specific principles and constraints, leading to more sustainable and impactful designs aligned with industry standards and project requirements.

The convergence of AI and design has brought about a paradigm shift in DGMs with the advent of language models. These models offer new possibilities for exploration, diverse design generation, and innovation. However, challenges include designs that may not consider practical constraints, requiring human oversight. Responsible and ethical use of language models is crucial for ensuring designs align with safety, inclusivity, and environmental considerations in DGMs.

Conclusions

This review has delved into the expansive realm of DGMs within the architectural design sector, highlighting their promising yet intricate capabilities. While our exploration has extended the ways in which DGMs can potentially streamline design processes and foster innovation, it is crucial to underscore that the transformative potential of DGMs is derived from both established applications and forward-looking possibilities, rather than conclusive proof across the board.

The discussion on the utility and flexibility of DGMs indeed illuminates a path toward significant advancements in design methodologies, underscored by examples of efficiency gains, creative enhancements, and sustainability impacts. However, the journey from potential to proven impact is paved with challenges including data quality, performance evaluation, computational complexity, creativity limitations, interpretability concerns, and the imperative need for interdisciplinary collaboration have been identified. Recognizing these challenges is crucial for charting the course of future research endeavors. It is imperative that future investigations prioritize advancements in hardware capabilities and utilize the potential of language models to overcome existing barriers.

The industry can unlock the full potential of DGMs by addressing the challenges. The future trajectory of DGMs in the construction sector relies on a delicate balance between creativity, optimization, and human expertise. This synthesis has the potential to initiate a paradigm shift, fundamentally transforming the construction landscape and shaping a built environment that adeptly meets the intricate and evolving needs of society.

Essentially, as we navigate the evolving frontier of DGMs in the construction domain, it becomes evident that their impact extends beyond mere technological advancements. DGMs have the power to contribute meaningfully to the creation of adaptive and user-centric built environments, embodying a symbiosis between cutting-edge technology and human ingenuity. The collective efforts of researchers, practitioners, and stakeholders are instrumental in utilizing this potential, ensuring that the future of DGMs in construction is not only transformative but also socially responsible and sustainable. The path forward requires a clear-eyed focus on evidence-based advancements, collaborative innovation, and the responsible harnessing of capabilities of DGMs to meet the dynamic needs of society and the built environment.

Acknowledgments

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References

Bourahla, N., Tafraout, S., Bourahla, Y., Sereir-El-Hirtsi, A., Skoudarli, A., 2022. GA based design automation and optimization of earthquake resisting CFS structures in a BIM environment. Structures 43, 1334–1341. https://doi.org/10.1016/J.ISTRUC.2022.07.041

Chaillou, S., 2020. ArchiGAN: Artificial Intelligence x Architecture. Architectural Intelligence 117–127. https://doi.org/10.1007/978-981-15-6568-7_8

Chaillou, S., 2019. AI + Architecture | Towards a New Approach. Harvard University.

Cui, H., Turan, O., Sayer, P., 2012. Learning-based ship design optimization approach. Computer-Aided Design 44, 186–195. https://doi.org/10.1016/J.CAD.2011.06.011

Czerniawski, T., Ma, J.W., Fernanda Leite, 2021. Automated building change detection with amodal completion of point clouds. Autom Constr 124, 103568. https://doi.org/https://doi.org/10.1016/j.autcon.2021.103568

Danhaive, R., Mueller, C.T., 2021. Design subspace learning: Structural design space exploration using performance-conditioned generative modeling. Autom Constr 127, 103664. https://doi.org/10.1016/j.autcon.2021.103664

Dworschak, F., Dietze, S., Wittmann, M., Schleich, B., Wartzack, S., 2022. Reinforcement Learning for Engineering Design Automation. Advanced engineering informatics 52. https://doi.org/10.1016/j.aei.2022.101612

Finch – Optimizing Architecture [WWW Document], n.d. URL https://www.finch3d.com/ (accessed 5.26.23).

Ghannad, P., Lee, Y.-C., Asce, A.M., Turner, B.S., 2021. Developing an Advanced Automated Modular Housing Design System Using Deep Learning and Building Information Modeling (BIM). Computing in Civil Engineering 2021 - Selected Papers from the ASCE International Conference on Computing in Civil Engineering 2021 587–595. https://doi.org/10.1061/9780784483893.073

Girdhar, R., 2016. Learning a Predictable and Generative Vector Representation for Objects. CoRR abs/1603.08637.

Hayashi, K., Ohsaki, M., 2021. Reinforcement learning for optimum design of a plane frame under static loads 37, 1999–2011. https://doi.org/10.1007/s00366-019-00926-7

Higharc – The intelligent homebuilding platform. [WWW Document], n.d. URL https://www.higharc.com/ (accessed 5.26.23).

Isola, P., Zhu, J.Y., Zhou, T., Efros, A.A., 2016. Image-to-Image Translation with Conditional Adversarial Networks. Proceedings - 30th IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017 2017-January, 5967–5976. https://doi.org/10.1109/CVPR.2017.632

Jeong, J.H., Jo, H., 2021. Deep reinforcement learning for automated design of reinforced concrete structures. Computer-Aided Civil and Infrastructure Engineering 36, 1508–1529. https://doi.org/10.1111/MICE.12773

Jiang, S., Wang, M., Ma, L., 2023. Gaps and requirements for applying automatic architectural design to building renovation. Autom Constr 147. https://doi.org/10.1016/j.autcon.2023.104742

Kaelbling, L.P., Littman, M.L., Moore, A.W., 1996. Reinforcement Learning: A Survey. Journal of Artificial Intelligence Research 4, 237–285. https://doi.org/10.1613/JAIR.301

Karan, E., Asadi, S., 2019. Intelligent designer: A computational approach to automating design of windows in buildings. Autom Constr 102, 160–169. https://doi.org/10.1016/j.autcon.2019.02.019

Karras, T., Laine, S., Aittala, M., Hellsten, J., Lehtinen, J., Aila, T., 2019. Analyzing and Improving the Image Quality of StyleGAN. Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition 8107–8116. https://doi.org/10.1109/CVPR42600.2020.00813

Kingma, D.P., Welling, M., 2013. Auto-Encoding Variational Bayes. 2nd International Conference on Learning Representations, ICLR 2014 - Conference Track Proceedings.

Kookalani, S., Cheng, B., 2022. Structural performance prediction of GFRP elastic gridshell structures by artificial neural network, in: 6th International Conference on Applied Researches in Science and Engineering. Aachen, Germany.

Kookalani, S., Cheng, B., 2021a. Structural Analysis of GFRP Elastic Gridshell Structures by Particle Swarm Optimization and Least Square Support Vector Machine Algorithms. Journal of Civil Engineering and Materials Application 5, 139–150. https://doi.org/10.22034/JCEMA.2021.304981.1064

Kookalani, S., Cheng, B., 2021b. Parametric-insensitive nonparallel support vector regression for structural stress prediction of GFRP elastic gridshell structures, in: International Conference on New Research and Achievements in Science, Engineering and Technologies. Seoul, South Korea.

Kookalani, S., Cheng, B., Torres, J.L.C., 2022a. Structural performance assessment of GFRP elastic gridshells by machine learning interpretability methods. Frontiers of Structural and Civil Engineering 16, 1249–1266. https://doi.org/10.1007/s11709-022-0858-5

Kookalani, S., Cheng, B., Xiang, S., 2021. Shape optimization of GFRP elastic gridshells by the weighted Lagrange ε-twin support vector machine and multi-objective particle swarm optimization algorithm considering structural weight. Structures 33, 2066–2084. https://doi.org/10.1016/j.istruc.2021.05.077

Kookalani, S., Nyunn, S., Xiang, S., 2022b. Form-finding of lifting self-forming GFRP elastic gridshells based on machine learning interpretability methods. STRUCTURAL ENGINEERING AND MECHANICS 84, 605–618.

Lagaros, N.D., Papadrakakis, M., 2012. Applied soft computing for optimum design of structures. Structural and Multidisciplinary Optimization 45, 787–799. https://doi.org/10.1007/S00158-011-0741-9

Lee, X.Y., Balu, A., Stoecklein, D., Ganapathysubramanian Baskar, Sarkar Soumik, 2019. A case study of deep reinforcement learning for engineering design: Application to microfluidic devices for flow sculpting. Journal of mechanical design 141. https://doi.org/https://doi.org/10.1115/1.4044397

Li, M., Liu, Y., Wong, B.C.L., Gan, V.J.L., Cheng, J.C.P., 2023. Automated structural design optimization of steel reinforcement using graph neural network and exploratory genetic algorithms. Autom Constr 146, 104677. https://doi.org/10.1016/j.autcon.2022.104677

Liao, W., Huang, Y., Zheng, Z., Lu, X., 2022. Intelligent generative structural design method for shear wall building based on “fused-text-image-to-image” generative adversarial networks. Expert Syst Appl 210, 118530. https://doi.org/10.1016/J.ESWA.2022.118530

Liao, W., Lu, X., Huang, Y., Zheng, Z., Lin, Y., 2021. Automated structural design of shear wall residential buildings using generative adversarial networks. Autom Constr 132, 103931. https://doi.org/10.1016/J.AUTCON.2021.103931

Liu, J., Liu, P., Feng, L., Wu, W., Li, D., Chen, Y.F., 2020. Automated clash resolution for reinforcement steel design in concrete frames via Q-learning and Building Information Modeling. Autom Constr 112. https://doi.org/10.1016/j.autcon.2019.103062

Lu, X., Liao, W., Zhang, Y., Huang, Y., 2022. Intelligent structural design of shear wall residence using physics-enhanced generative adversarial networks. Earthq Eng Struct Dyn 51, 1657–1676. https://doi.org/10.1002/EQE.3632

Maghami, A., Hosseini, M., 2022. Automated design of phononic crystals under thermoelastic wave propagation through deep reinforcement learning. Eng Struct 263. https://doi.org/10.1016/j.engstruct.2022.114385

Mirra, G., Pugnale, A., 2021. Comparison between human-defined and AI-generated design spaces for the optimisation of shell structures. Structures 34, 2950–2961. https://doi.org/https://doi.org/10.1016/j.istruc.2021.09.058

Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A.A., Veness, J., Bellemare, M.G., Graves, A., Riedmiller, M., Fidjeland, A.K., Ostrovski, G., Petersen, S., Beattie, C., Sadik, A., Antonoglou, I., King, H., Kumaran, D., Wierstra, D., Legg, S., Hassabis, D., 2015. Human-level control through deep reinforcement learning. Nature 2015 518:7540 518, 529–533. https://doi.org/10.1038/nature14236

Nauata, N., Chang, K.H., Cheng, C.Y., Mori, G., Furukawa, Y., 2020. House-GAN: Relational Generative Adversarial Networks for Graph-constrained House Layout Generation. Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics) 12346 LNCS, 162–177. https://doi.org/10.1007/978-3-030-58452-8_10

Nauata, N., Hosseini, S., Chang, K.H., Chu, H., Cheng, C.Y., Furukawa, Y., 2021. House-GaN++: Generative adversarial layout refinement network towards intelligent computational agent for professional architects. Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition 13627–13636. https://doi.org/10.1109/CVPR46437.2021.01342

Pan, Y., Zhang, L., 2021. Roles of artificial intelligence in construction engineering and management: A critical review and future trends. Autom Constr 122, 103517. https://doi.org/10.1016/J.AUTCON.2020.103517

Park, T., Liu, M.Y., Wang, T.C., Zhu, J.Y., 2019. Semantic Image Synthesis with Spatially-Adaptive Normalization. Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition 2019-June, 2332–2341. https://doi.org/10.1109/CVPR.2019.00244

Qian, W., Xu, Y., Li, H., 2022. A self-sparse generative adversarial network for autonomous early-stage design of architectural sketches. Computer-Aided Civil and Infrastructure Engineering 37, 612–628. https://doi.org/10.1111/MICE.12759

Qian, W., Yang, F., Mei, H., Li, H., 2023. Artificial intelligence-designer for high-rise building sketches with user preferences. Eng Struct 275, 115171. https://doi.org/10.1016/J.ENGSTRUCT.2022.115171

Rigger, E., Shea, K., Stankovic, T., 2018. Task categorisation for identification of design automation opportunities. Journal of Engineering Design 29, 131–159. https://doi.org/10.1080/09544828.2018.1448927

Sharma, A., Grau, O., Fritz, M., 2016. VConv-DAE: Deep volumetric shape learning without object labels. Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics) 9915 LNCS, 236–250. https://doi.org/10.1007/978-3-319-49409-8_20/TABLES/6

Shi, F., Soman, R.K., Han, J., Whyte, J.K., 2020. Addressing adjacency constraints in rectangular floor plans using Monte-Carlo Tree Search. Autom Constr 115. https://doi.org/10.1016/j.autcon.2020.103187

Soltani, A.A., Huang, H., Wu, J., Kulkarni, T.D., Tenenbaum, J.B., 2017. Synthesizing 3D shapes via modeling multi-view depth maps and silhouettes with deep generative networks. Proceedings - 30th IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017 2017-January, 2511–2519. https://doi.org/10.1109/CVPR.2017.269

Steuben, J.C., Iliopoulos, A.P., Michopoulos, J.G., 2016. Implicit slicing for functionally tailored additive manufacturing. Computer-Aided Design 77, 107–119. https://doi.org/10.1016/J.CAD.2016.04.003

Sun, H., Ma, L., 2020. Generative Design by Using Exploration Approaches of Reinforcement Learning in Density-Based Structural Topology Optimization. Designs 2020, Vol. 4, Page 10 4, 10. https://doi.org/10.3390/DESIGNS4020010

Tan, Q., Gao, L., Lai, Y.K., Xia, S., 2017. Variational Autoencoders for Deforming 3D Mesh Models. Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition 5841–5850. https://doi.org/10.1109/CVPR.2018.00612

Torky, A.A., Aburawwash, A.A., 2018. A Deep Learning Approach to Automated Structural Engineering of Prestressed Members. International Journal of Structural and Civil Engineering Research 347–352. https://doi.org/10.18178/IJSCER.7.4.347-352

Wang, H., Wang, Jia, Wang, Jialin, Zhao, M., Zhang, W., Zhang, F., Xie, X., Guo, M., 2017. GraphGAN: Graph representation learning with generative adversarial nets, in: The 32nd AAAI Conference on Artificial Intelligence (AAAI).

Weng, X., Huang, Y., Li, Y., Yang, H., Yu, S., 2023. Unsupervised domain adaptation for crack detection. Autom Constr 153, 104939. https://doi.org/https://doi.org/10.1016/j.autcon.2023.104939

Wu, A.N., Stouffs, R., Biljecki, F., 2022. Generative Adversarial Networks in the built environment: A comprehensive review of the application of GANs across data types and scales. Build Environ 223, 109477. https://doi.org/10.1016/j.buildenv.2022.109477

Wu, W., Fu, X.M., Tang, R., Wang, Y., Qi, Y.H., Liu, L., 2019. Data-driven interior plan generation for residential buildings. ACM Transactions on Graphics (TOG) 38, 12. https://doi.org/10.1145/3355089.3356556

Xu, T., Zhang, P., Huang, Q., Zhang, H., Gan, Z., Huang, X., He, X., 2017. AttnGAN: Fine-Grained Text to Image Generation with Attentional Generative Adversarial Networks. Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition 1316–1324. https://doi.org/10.1109/CVPR.2018.00143

Yonekura, K., Hattori, H., 2019. Framework for design optimization using deep reinforcement learning. Structural and Multidisciplinary Optimization 60, 1709–1713. https://doi.org/10.1007/S00158-019-02276-W/FIGURES/2

Yoo, S., Lee, S., Kim, S., Hwang, K.H., Park, J.H., Kang, N., 2021. Integrating deep learning into CAD/CAE system: generative design and evaluation of 3D conceptual wheel. Structural and Multidisciplinary Optimization 64, 2725–2747. https://doi.org/10.1007/S00158-021-02953-9/FIGURES/30

Zhang, J., Guo, X., Zong, S., 2023. Implicit parametric modal expansion method for single-layer reticulated shells based on generative adversarial network. Structures 54, 1676–1689. https://doi.org/10.1016/J.ISTRUC.2023.05.151

Zhang, Y., Mueller, C., 2017. Shear wall layout optimization for conceptual design of tall buildings. Eng Struct 140, 225–240. https://doi.org/10.1016/J.ENGSTRUCT.2017.02.059

Zhao, P., Liao, W., Huang, Y., Lu, X., 2023. Intelligent design of shear wall layout based on attention-enhanced generative adversarial network. Eng Struct 274, 115170. https://doi.org/10.1016/J.ENGSTRUCT.2022.115170

Zhao, P., Liao, W., Xue, H., Lu, X., 2022. Intelligent design method for beam and slab of shear wall structure based on deep learning. Journal of building engineering 57. https://doi.org/10.1016/j.jobe.2022.104838

Zhu, J.Y., Park, T., Isola, P., Efros, A.A., 2017. Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks. Proceedings of the IEEE International Conference on Computer Vision 2017-October, 2242–2251. https://doi.org/10.1109/ICCV.2017.244