State-of-the-art review of automated structural design optimization

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ABSTRACT: Automated and intelligent structural design optimization has been a heated research topic in structural engineering community. The automated structural design may learn from existing design drawings and finite element models of previous design, infuse design experts' knowledge with design standards and codes, and notably reduce the time and difficulty of structural design compared to conventional approach. This study provides a review of current automated structural design optimization approaches, which may be categorized as the approaches based on finite element model and the deep-learning approach based on human design dataset. For the design optimization based on finite element model, the gradient-based algorithm and gradient-free algorithm are illustrated and compared. The selection of objective function and constraint functions for structural design optimization are summarized. The parallel computing method developed based on high-performance computing resources are also summarized. In addition, the deep learning approaches, which directly generate preliminary structural design drawings based son architectural drawings and datasets of human design results are also summarized. Major architectures in this research field are discussed, including generative adversarial networks (GAN), diffusion models and Variational Auto-Encoder (VAE). The combination between deep learning approach and conventional finite-element model-based approach are also discussed and the future development trends and potential challenges are discussed.

1. INTRODUCTION

How to achieve the automated design of engineering structures has been a heated research topic in the civil engineering research field. Currently, the design of engineering structures mostly relies on engineers' experience and heuristics, which may be time-consuming and may not obtain an optimized design of engineering structures, while the implementation of computational design optimization of engineering structures is rarely adopted in real projects. Recently, high-performance materials and smart materials are also rapidly developed and implemented in engineering structures, including high-strength steel, low-yield-point steel, ultra-high-performance concrete (UHPC), and Engineered Cementitious Composite (ECC). In addition, many novel structural components have also been proposed and become available in design practice, including but not limited to steel-concrete composite shear walls, Magnetorheological dampers, variable-friction dampers (Spencer & Nagarajaiah, 2003), metamaterial-based foundations (Witarto et al., 2019) and metamaterial-based barriers (Zhang et al., 2022). The reasonable design adopting these new material and new components considering the complicated load are still challenging due to a lack of engineering experience and lack of design standards. Therefore, computational design optimization is strongly needed for the development of engineering structures with novel materials and components.

Computational design optimization of engineering structures currently relies on finite element (FE) software and gradient-free optimization algorithms. First, researchers and designers need to select a few typical design parameters to represent the structural design, such as location and number of energy-dissipation dampers and shear wall thickness. Second, linear or nonlinear finite element simulations of structures are conducted to obtain the mechanical performance of structures with certain parameters. Typical metrics of structures can be obtained, such as maximum lateral drift ratio under seismic excitation, damage variables of concrete and steel under seismic loads, material and labour cost during construction, and CO_2 emission during construction. Subsequently, gradient-free optimization algorithms are adopted by many researchers for computational design optimization. However, the gradient information of structural performance metrics to design parameters may be hard to obtain through the conventional FE modelling approach, thereby notably restricting the development of gradient-based optimization in structural engineering. In addition, gradient-free optimization typically requires a relatively less number of design parameters to be included, which may restrict the search domain of parameters and thereby limit the performance of design results.

In addition to computational design optimization, intelligent design has also emerged in civil engineering to serve as an alternative for engineers to obtain the preliminary design of engineering structures. With the rapid design of artificial intelligence (AI), generative adversarial networks (GANs) have been adopted for the intelligent design of shear walls (Lu et al., 2022b) and floor systems of building structures considering seismic loads. Deep-learning-based models were trained based on structural design datasets and were adopted to generate design drawings and three-dimensional design models of engineering structures to replicate human designers' drawings. In addition, the design standards, the engineers' experience and the physical loss were also infused into AI-based design systems, which may further enhance the performance of AI-based design systems. In this study, recent typical development in computational design optimization and AI-based design are summarized and reviewed.

2. FE SIMULATION-BASED COMPUTATIONAL DESIGN OPTIMIZATION

FE simulation-based computational design optimization has been a heated research topic in the civil engineering research field, including buildings and bridges and covering the design of new structures and retrofitting design of existing structures. In FE simulation, the fibre beam-column elements were widely used to simulate framed members while the slabs may be simulated by equivalent constraints, shell elements or solid elements. For new structures, the objective is to reduce construction costs while meeting design standards. For existing structures, the objective is to obtain a reasonable retrofitting design with reduced construction cost and retrofitting time. The typical recent development of building structures is summarized below.

2.1. *Computational design optimization of structures with the gradient-free algorithms*

Typical gradient-free optimisation algorithms include genetic algorithm (GA) and particle swarm approach (PSO), while many other gradient-free optimization algorithms are also available for structural optimization. The motivation for adopting a gradient-free optimization algorithm is that the gradient information of the solution field of FE analysis with respect to design input variables may be hard to obtain, especially for design optimization considering the location of structural components as discrete variables. Both GA and PSO are also classified into population-based optimization methods and have been adopted in structural optimization research (Kashani et al., 2022). The concept of GA is to simulate the natural evolution of animals and the survival of the fittest. For the GA algorithm, the initial population was first generated and the fitness (i.e. objective function) of each individual was evaluated and ranked. In each step, the individuals with higher fitness were selected with higher probabilities. Subsequently, the crossover operator combined the genetics of parents to generate a new population until convergence. Generally, the fitness of the population will increase in the training process and higher fitness values can be obtained upon convergence. Cazacu and

Grama (2014) reported GA optimization for the minimization of the self-weight of truss structures. An innovative encoding scheme was proposed for truss structures, which allows for simultaneous updating of the topology, shape and cross-section of truss elements. Based on the optimization results, the encoding technique can automatically find the optimized location of truss elements in the truss structure.

PSO was proposed by Kennedy and Eberhart (1995). In PSO, a solution is defined as a particle and a population of the solution is termed a swarm of particles. Each particle has a position and velocity. In each step, the best position of each particle and the best position of the swarm are updated. The velocity of each particle was adjusted according to the memory of the particle and swarm. The original form of PSO is suitable for continuous parameters while GA can be applied to both continuous parameters and discrete parameters. A pioneering study was reported by Perez and Behdinan (2007), who adopted PSO for the optimization of three benchmark tasks. Based on PSO, three typical structures were optimized and the constraints were applied to the optimization problem, including a 10-bar truss, a 25-bar truss and a 72-bar truss. In all three problems, the cross-sectional area of each truss member in the structure was optimized towards the minimized total weight while meeting the allowable stress requirement and displacement requirement. Based on the training results, the PSO algorithm showed the ability to obtain the optimal design of these truss structures compared to other structural optimization methods. Fitas et al. (2022) combined the PSO algorithm with fitness assignment methods and elitist strategies and developed a multi-objective PSO method. The proposed method was implemented and used for the optimization problem of a cylindrical shell composed of composite material to reduce the self-weight.

In computational structural design optimisation, when the location of typical components (i.e. buckling-restraint bracings and dampers) needs to be optimized, the locations are typically considered discrete parameters. Considering discrete variables, Discrete PSO (DPSO) was also proposed by researchers (D. Wang et al., 2018), and some related references adopt DPSO in structural design optimization (Kaveh & Zolghadr, 2014; Shojaee et al., 2013). In comparison, GA may naturally consider discrete variables in its original formulation. In addition, the computational cost of GA is typically higher than that of PSO for larger population sizes.

2.2. *Computational design optimization of structures with gradient-based algorithms*

Wang and Mahin (2018a) conducted a case study on a prototype 35-story steel moment-resisting frame with pre-Northridge beam-column connections based on a three-dimensional (3D) FE model in OpenSEES. The retrofitting design of the prototype building was considered by adding fluid viscous dampers (FVDs) in the moment-resisting frame. The nonlinear fibre beam-column elements were adopted to simulate the beams and columns and the moment-curvature relationship of beam-column connections was considered. A total of 11 typical ground motions were adopted for FE simulation. The location and effective damping ratios of fluid viscous dampers (FVDs) were considered as parameters for optimization. The objective function included both the inter-story drift ratios and the maximum peak story accelerations. The constraint function included the peak inter-story drift, peak floor acceleration, maximum damper force and damper displacement. The gradient-based algorithm in Matlab software was adopted for design optimization. However, the gradient information of the objective function and constraint function with respect to the design parameters were obtained based on the finite difference because FE simulations were hard to directly obtain the gradient information. Compared to manual design, the maximum value of peak inter-story drifts reduced from 1.48% to 1.02% based on the optimisation process. In addition, Wang and Mahin (2018b) further compared the retrofitting of the 35-story prototype frame with various energy-dissipation components, including FVDs, viscous wall dampers and buckling restrained braces. Based on nonlinear FE simulation results, the FVD-based retrofitting design achieved the best mechanical performance with the best cost-effective results. It was also concluded that the design optimization based on FE model was limited to relatively few number of parameters. Because of the high computational cost, FE simulation-based design optimization considering more than 10 parameters were rarely reported in literatures. In addition, the retrofitting optimization results are still case-sensitive, and the knowledge learned from a prototype building may not transfer to other buildings.

The implementation of nonlinear FE analysis considering geometrical and material nonlinearity and the elaborate FE model adopting shell elements and truss elements are still challenging currently. In addition, because a large amount of FE simulations need to be run, the design optimization needs to adopt both open-source software (i.e. OpenSEES) and a supercomputer to reduce the computation time. The FE-based design optimization adopting commercial software is relatively less reported in the literature due to the limited availability of licenses.

3. INTELLIGENT OPTIMIZATION OF STRUCTURES

3.1. *Generative models*

With the rapid development of deep learning, deep generative models were developed by many researchers and three typical models are variational autoencoders (VAEs, Kingma and Welling (2019)), generative adversarial networks (GANs, Goodfellow et al. (2014)) and diffusion models (Rombach et al., 2022). Among these models, GANs have been successfully implemented for the intelligent design of building structures based on a dataset composed of structural design drawings and architecture design drawings in recent research, while diffusion models may also be applied for the intelligent design of engineering structures in the future. Generative models achieve significant success in generating photo-realistic images, speech generation and video generation. The training process of GANs includes training of the generator G and discriminator D . The discriminator was trained to maximize the classification accuracy to tell the artificial data from true data, while the generator was trained to confuse the discriminator, which is training for $\max_{\mathrm{D}} \min_{\mathrm{G}} V(\mathrm{G},\mathrm{D})$ where V is defined as follows as summarized by Creswell et al. (2018):

$$V(\mathrm{G},\mathrm{D}) = \mathrm{E}_{p_{\text{data}}(\mathbf{x})} \log \mathrm{D}(\mathbf{x}) + \mathrm{E}_{p_g(\mathbf{x})} \log(1-\mathrm{D}(\mathbf{x})) \tag{1}$$

In the practical study, both the generator and the discriminator widely adopt neural networks.

3.2. *Learning from design drawings*

GAN has already been adopted for intelligent architectural design and StructGAN (Liao et al., 2021) was proposed to achieve the automated design of shear wall structures based on the design drawing dataset. Figure 1 shows the schematic plot of StructGAN (Liao et al., 2021). As shown in Figure 1, a large dataset of structural design drawing documents was collected first based on the Chinese design of real building structures with reinforced concrete (RC) shear walls. For each engineering project, the architectural drawings from architectural companies and the structural design drawings were obtained. The architectural drawings were pre-processed to remove additional text in the drawings and only keep the basic information of shear walls (i.e. location of shear walls and location of openings). For each structure, the structural design drawings were also obtained from the design company. For structural design drawings, various colours were used to represent the shear walls and various non-structural components (i.e. infill wall, window and gate). In addition, the datasets are classified based on the different heights of building structures. After pre-processing the dataset, StructGAN was trained to generate the structural design drawings based on architectural design drawings. The original StructGAN adopted the convolutional neural network architecture of pix2pixHD (T. Wang et al., 2018) for the generative network, and the data augmentation methods were also included (flip and rotation of the images). After the training process of StructGAN is complete, Civil engineers are invited to judge if the drawings were generated by StructGAN or the engineer and score the design outcomes based on experience. FE model of StructGAN design and Engineer design was established to compare story drift ratio and seismic repair costs. Based on the comparison of FE simulation results, the lateral drift ratio under seismic excitation of StructGAN prediction is very similar to that of human design results from experienced civil engineers. Compared to the human design by civil engineers, StructGAN achieved more than 10 times speedup while the seismic loss evaluated using FEMA P58 (2018) methodology increased by 6% only for a typical design of the structure.

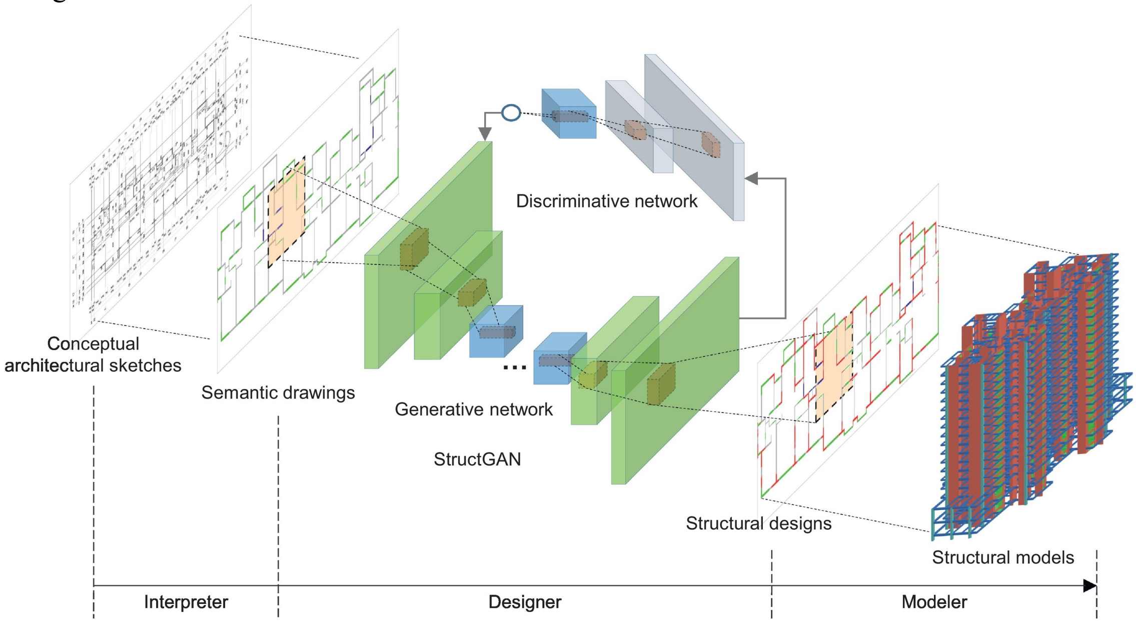

Figure 1 Schematic plot of StructGAN (reprinted from Liao et al. (2021) with permissions from the publisher)

In addition to shear wall structures, Zhao et al. (2022) extended the application of StructGAN to include beams and slabs in shear wall structures. Compared to shear walls under earthquake load, static load and live load, the beams and slabs are typically designed to resist the vertical load due to static load and live load. Therefore, the dataset for the beam and slab design of the floor system was established and the building space attributes were marked by the colour of each room. The building space attributes are related to the design vertical load of each room. Subsequently, StructGAN were trained to generate the cross-section height of the coupling beams, frame beams and slabs in the shear wall structures. Subsequently, automated reinforcement design tools in design software such as ETABS can be used to obtain the detailed reinforcement information of each beam and slab. Based on the StructGAN design outcome and survey conducted for human experts, 51.43% of engineer designs were judged as “Engineer’s design” by human experts, while 45.26% of deep-learning-based designs were judged as “Engineer’s design” by human experts. In addition, the difference in vertical displacement of the system designed by engineers and AI was negligible.

3.3. *Learning from design drawings and physics-law*

For intelligent design, the AI model can be regularized by the physical response or mechanical response of engineering structures. Lu et al. (2022a) proposed a physics-enhanced GAN model (StructGAN-PHY) for the intelligent design of engineering structures that can automatically mitigate the seismic response and reduce seismic loss. Figure 2 shows the schematic plot of the StructGAN-PHY model. As shown in Figure 2, in addition to the data-driven discriminator in StructGAN developed by Liao et al. (2021) evaluated based on a database of human design drawings, StructGAN-PHY added the physics estimator to predict the physical performance of structure design outcomes. To achieve an efficient estimate of physical response based on the generated design drawings in the training process, another database of seismic response was generated through a simplified stick model (i.e. multi-degree-of-freedom model). The CNN-based surrogate models were trained to predict the seismic response of building structures based on the design drawings on GPUs with notably reduced computational cost compared to CPU-based FE solvers. This step is similar to obtaining the objective function in computational structural optimization based on FE solvers reported in Section 2 of this paper. The physics loss was added to the data loss in the discriminator to obtain the total loss of the discriminator. Based on the training results, the StructGAN-PHY achieved notably reduced seismic response compared to the vanilla version of StructGAN. The StructGAN-PHY combined the StructGAN with an FE-based design optimization algorithm and is favourable for future extension to the intelligent design of problems with insufficient data of design drawings.

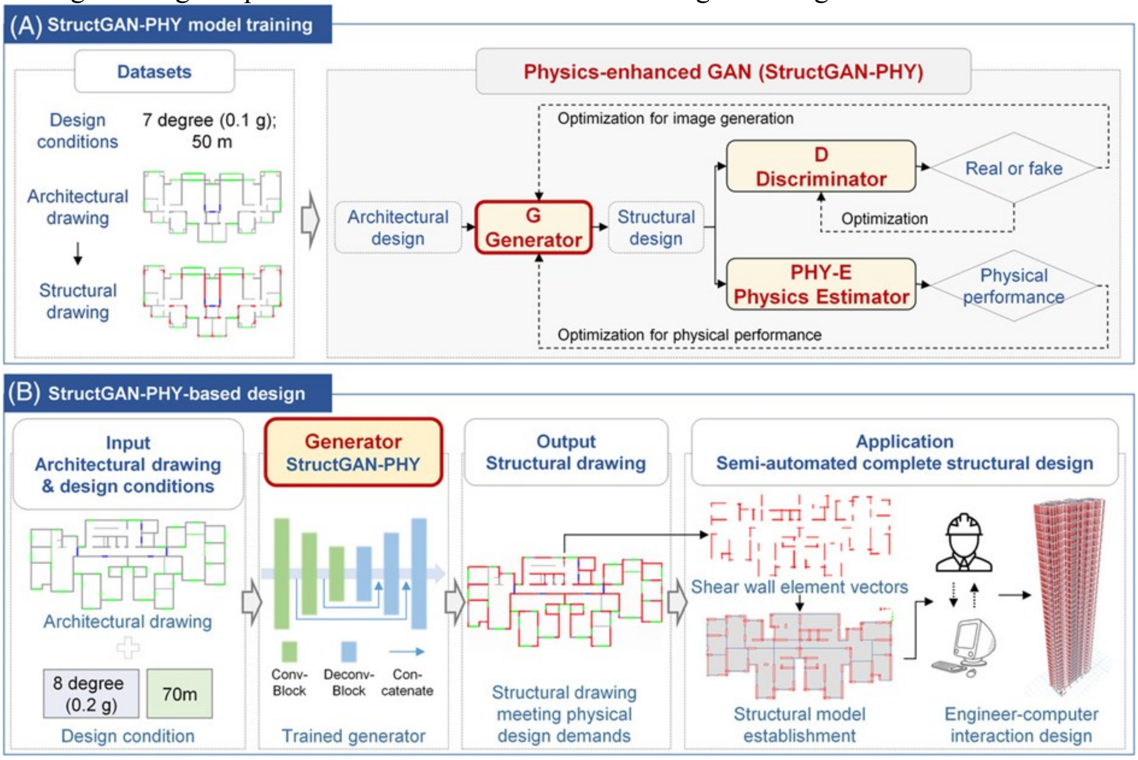

Figure 2 Schematic plot of StructGAN-PHY (reprinted from Lu et al. (2022a) with permissions from the publisher)

4. CONCLUSIONS AND DISCUSSION

This study provides a literature review of typical design optimization approaches in the civil engineering discipline including FE-based gradient-free optimization, FE-based gradient-based optimization and GAN-based intelligent design of engineering structures.

For FE-based structural optimization, the major challenge is that the gradient information of the solution field of FE simulations to design parameters may be hard to obtain, especially when a large number of design parameters were considered. Therefore, the majority of FE-based structural design optimization requires a preliminary selection of the most critical design parameters. For gradient-based optimization, both GA and PSO were widely reported in existing research. The structural design optimization mostly focused on truss elements and fibre beam-column elements with the linear material constitutive model. The elaborate FE models with nonlinear constitutive models are still challenging to be implemented in FE-based structural design.

For intelligent structural design optimization, the GAN model has been successfully implemented in the design of high-rise shear wall structures, including shear wall components, beams and slabs. The physics estimator has also been added as a novel discriminator to achieve physics-informed design optimization of structures.

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