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# Machine Learning in Structural Design: An Opinionated Review

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The prominence gained by Artificial Intelligence (AI) over all aspects of human activity today cannot be overstated. This technology is no newcomer to structural engineering, with logic-based AI systems used to carry out design explorations as early as the 1980s. Nevertheless, the advent of low-cost data collection and processing capabilities have granted new impetus and a degree of ubiquity to AI-based engineering solutions. This review paper ends by posing the question of how long will the human engineer be needed in structural design. However, the paper does not aim to answer this question, not least because all such predictions have a history of going wrong. Instead, the paper assumes throughout as valid the claim that the need for human engineers in conventional design practice has its days numbered. In order to build the case towards the final question, the paper starts with a general description of the currently available AI frameworks and their Machine Learning (ML) sub-classes. The paper then proceeds to review a selected number of studies on the application of AI in structural engineering design. A discussion of specific challenges and future needs is presented with emphasis on the much exalted roles of "engineering intuition" and "creativity". Finally, the conclusion section of the paper compiles the findings and outlines the challenges and future research directions.

**Keywords: artificial intelligence, machine learning, structural design, structural engineering, design space**



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## 1 INTRODUCTION

We call structural design the process by which the number, distribution, shape and size of structural elements, and their connectivity is determined so that a given design objective is achieved while meeting a number of constraints of serviceability and resistance. The objective can be the minimization of material consumption but in practice, it is more likely to be related to cost minimization and to involve trade-offs between manufacturing, logistical and sometimes sustainability considerations. At the beginning of the structural design process, human engineers are usually provided with the overall geometry—through Building Information Models (Jung and Joo, 2011), for example—and their task is to come up with specifications of the distribution of structural elements including their materials and sections. This process is carried out using a diverse collection of computational tools, from information modelling to structural analysis; sampling from catalogues involving hundreds of structural sections and with constant reference to thousands of pages of codes of practice. Consequently, as it stands today, structural design entails a significant and oftentimes tedious solution-searching process involving various complex and non-fully overlapping multi-dimensional domains, multiple constraints and large uncertainties, whereby arriving to a global optima would be a prohibitively time-consuming endeavour. Therefore, more often than not, the engineer's search will be brief and they will settle for the first sub-optimal design that satisfies all the hard constraints. Unsurprisingly, a range of tools have been proposed to carry out the optimization of some of the better-posed problems involving a relatively low number of structural elements, e.g., (Jewett and Carstensen, 2019; Amir and Shakour, 2018; Tsavdaridis et al., 2015); and more recently these tools have started to incorporate additional and more realistic complexities like dynamic actions (Giraldo-Londoño and Paulino, 2021), manufacturing processes (Zegard and Paulino, 2016; Carstensen, 2020), etc. However, the emphasis of this paper is not on the generation of targeted topology-optimized solutions for which excellent review articles can be found elsewhere, e.g., (Thomas et al., 2021). Instead, this opinionated review concentrates on the exploration of large and complex integrated design spaces with the aid of artificial intelligence (AI) and, more specifically, the increasing role that Machine Learning (ML) algorithms are playing in this search.

Artificial Intelligence (AI) is the branch of science that is concerned with the re-creation of human cognitive functions by artificial means. Although this is most commonly attempted via digital computers, other media, notably biological systems (Qian et al., 2011; Sarkar et al., 2021), have been and continue to be used with this purpose. This paper, however, focuses on the role of intelligent algorithms for digital computers; or more precisely, algorithms whose distinctive feature is their ability to learn. In this context, Machine Learning (ML) is a branch of AI whose central advantage is its potential to automatically detect patterns in data under uncertainty (Murphy, 2012). This uncertainty arises inevitably from the limited size of the datasets employed but it also reflects errors in data collection (including measurement) as well as hard epistemic paucities.

One of the first approaches to replicate human cognition was to organize "knowledge" as a collection of mutually related facts. Once a database of facts was built, so the belief went, inference rules could be used to query it, revealing the interconnections and allowing questions, including those related to engineering design, to be answered. The use of this type of AI in structural design was discussed as early as 1978 by Fenves and Norabhoompipat (1978) and application examples appeared in the early 1980s. For example, Bennett et al. (1978) developed a program consisting of 170 production rules and 140 consultation parameters to assist the engineer in the application of Finite Element Analysis (FEA) to the design of building structures. Also, Maher and Fenves (1985) constructed an expert system for the preliminary design of high-rise framed buildings. They used weighing factors to compare different gravity and lateral resisting structural systems highlighting the "best" design according to the criterion of a linear evaluation function. Other researchers like Ishizuka et al. (1981) used rule-based systems to infer seismic damage on the basis of a database of earthquake accelerograms and visual inspection reports. However, it soon became apparent that hard rules can not replicate the human inferential process and that their contribution to design would be limited, not least because the world for which engineers design is brimming with uncertainty but also because exceptions to the rule are all too common. Logic-based AI was abandoned.

With the passage of time, probabilistic reasoning made its way into ML and message passing architectures, which model intelligence on the basis of human neural information passing (Rumelhart et al., 1986), started to take the computational demands on storage and processing down to manageable levels. By the end of the 1980s, Bayesian Networks (BN) had become a practical scheme for ML (Pearl, 1988). BN have proven useful in evaluating the reliability of structures and infrastructure systems with multiple components and multiple failure sequences (Mahadevan et al., 2001). And Naive Bayes classifiers have been used to construct damage fragilities, e.g. (Kiani et al., 2019), predict the strength of structural components, e.g. (Mangalathu and Jeon, 2018), or estimate structural failure modes, e.g. (Mangalathu et al., 2020).

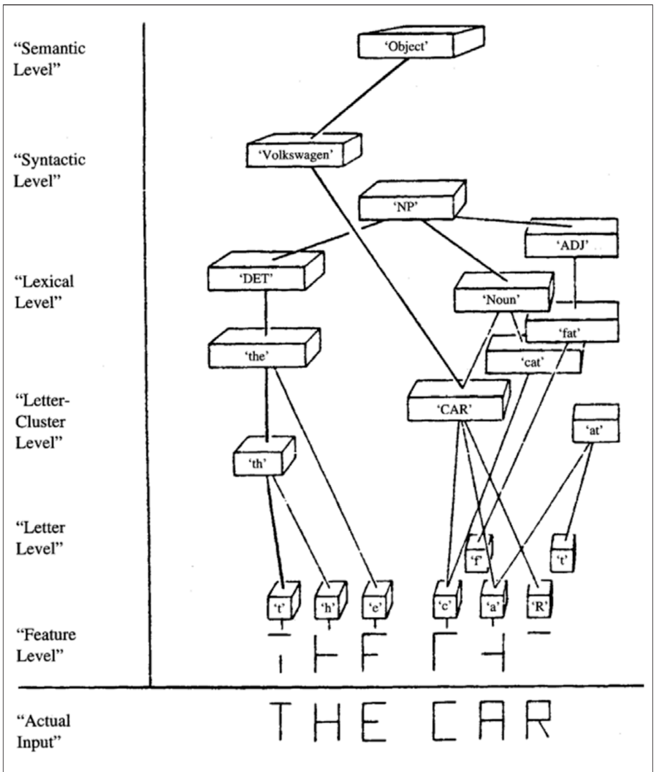


**FIGURE 1** | (Rumelhart, 1994) Message Center near the end of processing when the semantics of the imput have been well defined.

Meanwhile, Artificial Neural Networks, or Neural Networks (NN) for short, started to be used in all branches of engineering design. One of the first studies to apply back-propagation NN—an approach initially devised by Rumelhart et al. (1986)—to structural engineering was conducted by Vanluchene and Sun (1990). In their pioneering study, Vanluchene and Sun (1990) applied NN to the pattern recognition of a loaded beam, to the design of a simply supported reinforced concrete beam and to the structural analysis of a plate. NNs are abstractions of the functioning of the human brain that aim to replicate its ability to acquire knowledge through learning and storing in the form of interconnecting synaptic weights. In true fashion of the process originally hypothesised by Rumelhart et al. (**Figure 1**) the network takes a set of features as inputs and applies complex

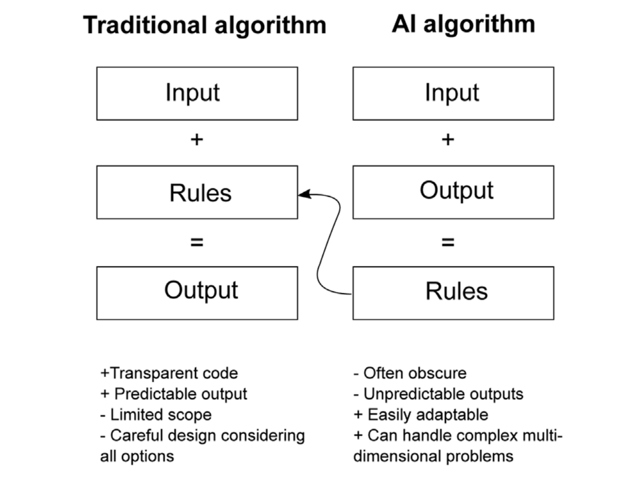


**FIGURE 2 |** Traditional vs. AI algorithms.

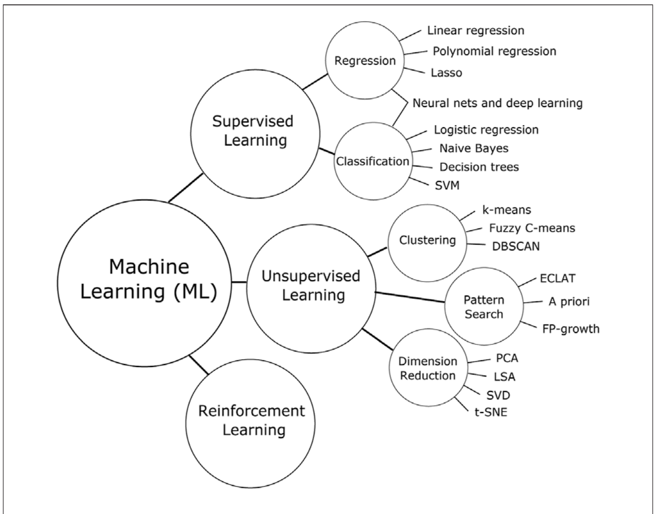


**FIGURE 3 |** Categories of ML algorithms.

feature fusion operations through a series of layers of neurons. The final layer outputs the end response either as a prediction or as a form of classification.

NN models (and their deep learning variants) have become extremely popular nowadays driven by the media coverage of their superb feature recognition capabilities and the notorious increase in computational power together with the wide accessibility of tools and libraries. Accordingly, NN have been used in seismic response prediction, e.g., Morfidis and Kostinakis (2017); Lagaros and Fragiadakis (2007), system identification, e.g., Sivandi-Pour et al. (2020), damage localization, e.g., Bani-Hani et al. (1999); Gharehbaghi et al. (2021) and in structural control, e.g., (Khalatbarisoltani et al., 2019; Suresh et al., 2010), among other structural engineering tasks. The literature on NN (and indeed ML) applications to structural engineering is vast. Sun et al. (2021) provide a comprehensive review of ML methods used to predict and asses structural performance and to identify structural conditions. Some of these can be used in support of structural design but do not directly deal with structural design *per se*, defined in the form presented earlier in this paper. In fact, issues related to ML and structural design, as defined above, are not particularly well covered in the literature despite the proven potential brought about by leveraging AI technologies and ML algorithms to improve the exploration of design alternatives beyond current human cognitive levels.

It follows from the previous discussion that existing design optimization methods concentrate on individual structural subassemblies and do not serve to automate the design of entire structures. By contrast, this paper will explore the use of ML algorithms to automate structural designs *stricto sensu*. To this end, this paper proceeds to review a selected number of studies on the application of ML in structural engineering design. A discussion of specific challenges and future needs is presented with emphasis on the much exalted roles of 'engineering intuition' and 'creativity'. Finally, the conclusion section of the paper compiles the findings and outlines the challenges and future research directions. But first, the paper will provide a general introduction to AI and ML methods.

## 2 BACKGROUND ON AI AND ML

As mentioned above, central to AI and ML algorithms is the ability to learn, potentially achieving the super-human ability of recognising patters in high-dimensional datasets that have remained impenetrable to the human mind. **Figure 2** compares the way traditional and AI software operate. In a traditional piece of software, the coder writes a "comprehensive" set of rules that the program must follow. Therefore, it is the sole responsibility of the programmer to consider all possible scenarios and to hard-code into the algorithm all the appropriate responses to these scenarios. It should be possible, in principle, to arrive to the precise output by following the path through the code given a specific input. By contrast, in AI algorithms the rules are created by the algorithm itself and the coder only provides the scaffold (or architecture) and feeds data into it. The AI algorithm will analyse the data and fill this scaffold with its own through training. Once those rules are established, they can then be used in the traditional way to predict other outputs given an input. The fact that the coder is exempt from considering and including all potential scenarios makes AI particularly useful when dealing with large datasets or complex processes.

The differences in construction and operation between traditional and AI software express themselves in a number of ways. Traditional code is naturally transparent and generally easy to predict while ML can be obscure and may produce unexpected results or include biases that are not always easy to detect. On the other hand, traditional algorithms will be limited to what the coder has predicted at first, while AI software is in principle easy to adapt without significant changes in the code. Traditional software demands the coder to capture carefully and accurately all the potential scenarios, while AI can handle complex problems

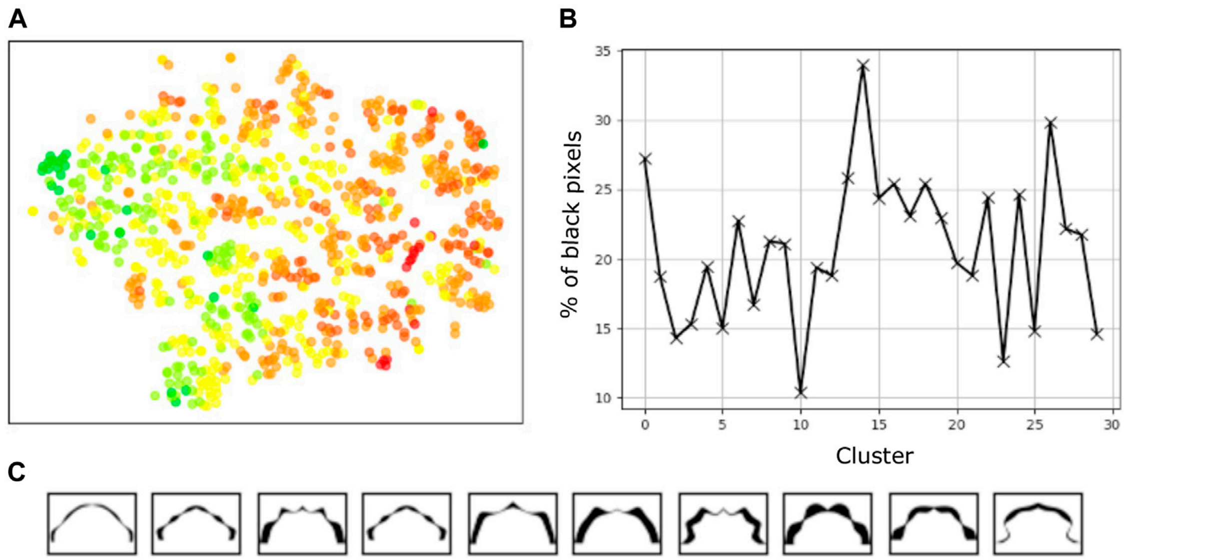


**FIGURE 4 |** Latent space representation of the data points coloured depending on the occupancy of the arches (a measure of the material usage) for the seismic design scenario. The latent space **(A)** is presented together with the plot of the mean occupancy of each cluster **(B)** and sample shapes from the best selected cluster **(C)**. Adapted from Palmeri et al. (2021) based on the CAE model of Maqdah et al. (2021).

more efficiently than humans, especially when they involve multiple dimensions or large datasets.

Broadly speaking, ML algorithms can be categorized in three main groups: supervised, unsupervised and reinforcement learning, depicted in **Figure 3**. Supervised learning is probably the closest to human learning. A series of "examples" is used by the ML algorithm to build "knowledge" about a given task in a similar way to how humans build and use "past experience" (Dietterich, 1996) like when small children are guided in their association of words to meanings. To this end, supervised models are given a set of features as input and labels as output. Then, the models attempt to find a set of rules to match a given set of features to the correct label guided by some measure of success. The process employs statistical methods for the learning operations and manual adjustments are usually not required. However, supervised ML relies on large amounts of correctly labelled input data, in quantities that can be significantly larger than those required by humans (Kühl et al., 2020).

On the other hand, unsupervised learning can be applied to different data types. In this approach, labels are not required, just features. The model is given those features and its algorithm then groups them according to some unknown property. In general, unsupervised models try to do one of three things: either cluster the data provided, find an anomaly in it, or reduce the number of dimensions in which to express the dataset. Grouping works by clustering data points that share some features without knowing what labels or indeed what categories are present. In anomaly detection or pattern recognition, a defining set of features is found and the model classifies the data point as either part of the set or as an anomaly. This is very helpful in failure identification or structural characterization. Reinforcement learning builds on these ideas and sometimes uses the algorithms developed for supervised and unsupervised learning. It is used in situations where it is difficult to get perfectly correct labels. In such cases, the algorithm is provided with an input and a reward function that gives an indication of how well or bad the algorithm is doing. The algorithm then learns how to maximise the reward.

In general, the creation of a typical AI algorithm involves four main stages. It starts with the data preparation. This is a crucial stage that can take longer than the others. It involves the acquisition of data, its analysis and pre-processing. The quality and quantity of data are determinant for a good output of the model. The second stage is the design of the model, which is followed by the third stage of training and evaluation. It is not uncommon that at the end of this process, the coder realises that changes are required in the data or the model architecture, and the design should be re-adjusted. Once the model is considered well designed and trained it is ready to enter its final stage of deployment.

## 3 AI AND THE DESIGN OF SPATIAL STRUCTURES

Although shells, vaults and other spatial structures are already among the most efficient structural forms and have a notoriously complex structural response, they have been fertile ground for many structural design optimization explorations. This may be because shells can be discretised as meshes with known support locations which, despite requiring hundreds of variables, are usually single-layered and lend themselves more easily to parametrization than the reticulated multi-storey frames with a multitude of potential element locations, sizes and connection types used in buildings. However, even if a highly parametrized design space is used, its sheer size still makes it trackless to the human mind. Therefore, the basic capability of machine learning to discover and rebuild complicated underlying connections between input and output variables from a relatively big dataset (Liu et al., 2020) can be of great use while designing spatial structures.

Mirra and Pugnale (2021) examined AI-generated design spaces built using Variational Autoencoder (VAE) models, and compared their outputs with those coming from a human-generated explicit definition of design variables. Two relatively simple but realistic cases were explored by Mirra and Pugnale involving triangular and square footprints. A dataset of 800 depth maps obtained from 3D models were used to train the VAE. Three objectives were set for the optimization, including: 1) the maximisation of the structural performance, quantified in terms of deformations obtained from Finite Element Analysis (FEA), 2) the maximisation of the height of the shell openings, and 3) the minimisation of the difference between the final and target footprints. They found that the AI-generated outputs had a greater diversity and responded better to the performance criteria in comparison with the solutions obtained from human-defined generative designs. Besides, AI solutions included structural configurations that would not have been possible to find within the human-defined design space. This hints to one of the main advantages of using AI in design: the possibility of exploring design options beyond those traditionally developed by human intelligence (Mueller, 2014).

The exploration of diverse design options brought about by AI was also exploited by Maqdah et al. (2021) and Palmeri et al. (2021) while studying the provision of structurally-efficient regolith-based arch forms for extraterrestrial construction. They built unsupervised machine learning models (Convolutional Autoencoders, CAE) capable of detecting patterns and differentiating between arch geometries and their stress and deformation contours (**Figure 4**). These models were then used to search for optimal sectional geometries considering the effects of extreme thermal changes and seismic action under low-gravity conditions. Various datasets, each one with over 500 thermal and static FEA analysis and a 60–40% training-validation split were constructed for this purpose. Although the optimal configurations found resembled those obtained by more traditional approaches (McLean et al., 2021), the possibility of including a diversity of design actions (gravity, thermal, and seismic) and a substantial number of dimensions that are then reduced to a smaller latent space where a holistic search process can be used was featured as a clear contribution of AI. Moreover, Maqdah et al. (2021) and Palmeri et al. (2021) were able to elucidate some of the dependencies of the latent space (reduced) dimensions on geometric and structural parameters which can be helpful in making informed (partially explainable) searches. Alongside the CAE, regression models were used to allow the visualisation of the changes in the arch shape and stress fields when moving towards a certain direction in the design space.

The works of Zheng et al. (2020) and Fuhrimann et al. (2018) have explored the use of ML in leveraging the fundamental relationship between force and form in shells. Zheng et al. (2020) trained a NN model to predict the relations between subdivision rules and structural and constructional performance metrics on the basis of graphic statics results. This surrogate use of ML models to enable a rapid exploration of design spaces constitutes one of many important attempts to improve the machine-human collaboration. Unfortunately, the parameters employed; notably for constructibility (i.e., number of faces with areas greater than a given threshold), may seem too simple proxies to capture the complexities of the manufacturing and construction challenges. On the other hand, Fuhrimann et al. (2018) also explored the potential of combining form-finding with ML in the form of Combinatorial Equilibrium Modelling and Self Organizing Maps. Central to these works is the need to grasp a complex space of solutions in order to both increase its diversity and to make it manageable to the designer.

The previously mentioned works have highlighted the basic capability of ML to discover and rebuild complicated underlying connections between input and output variables and to find relationships between structural shape and performance. Once those relationships are established, the corresponding optimization of the structural configuration is simplified (Liu et al., 2020). However, to set an optimization process where the design parameters are chosen automatically by the machine (algorithm) without human intervention remains difficult. This is because these parameters must exist in a low-dimensional space that can be optimized while not sacrificing their representational capacity. An issue that was also observed while optimizing the design of materials (Xue et al., 2020).

An alternative approach was followed by Danhaive and Mueller (2021) who tackled the design of a long span roof structure. For this purpose, they used variational auto encoders (VAE) to train low-dimensional (2D) models that are intuitive to explore by the human engineer. By conditioning the models on different performance indicators, the models can adapt their mappings. A new performance-driven sampling algorithm was proposed to generate databases that are biased towards design regions with high performing structures. The structural performance indicators employed in the case study are only mass dependent and are normalized so they are evenly distributed on the unit segment. A total of 36 design variables, mainly topological, were used in the design and dimensioning of the truss elements using the cross-section optimizer available in Karamba (Preisinger and Heimrath, 2014). The salient feature of this approach is that it gives the human designer a greater control over performance trade-offs standing in the middle between optimization methods, on the one side, and undirected search algorithms, on the other.

The support provided by ML algorithms to the design of spatial structures are not conscripted to structural calculations but can include the quantification of traditionally less quantifiable metrics such as aesthetics. For example, Zheng (2019) developed a NN that could be used to quantitatively evaluate the personal taste of an architect. By using force diagrams of polyhedral geometries with unique and distinguishable forms and a clear data structure and asking the human architect to score the inputs, a NN was trained to learn their design preferences. The results, which may seem unsurprising at first sight, put in evidence the capability of ML to express what may be considered as inexplicit. In doing so, Zheng demonstrated not only that solutions with

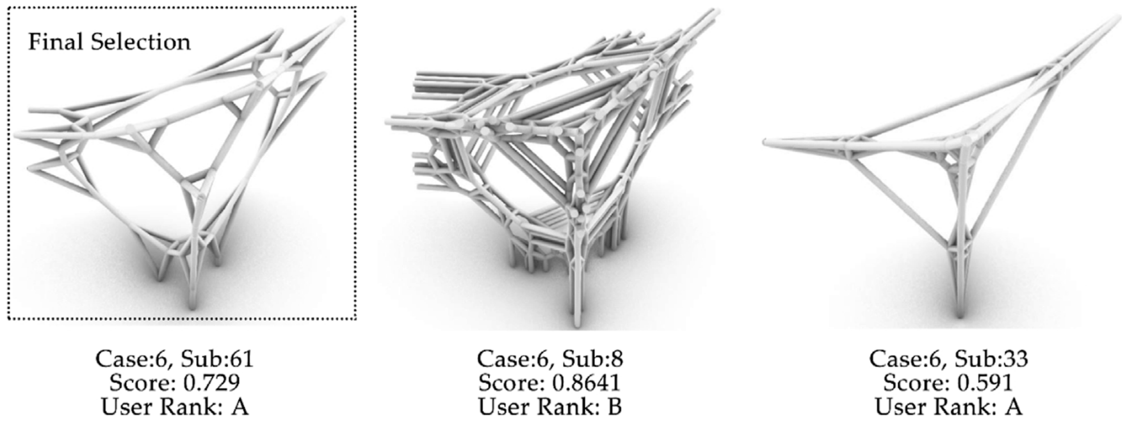


**FIGURE 5 |** Selection of form-found structures considering user taste by Zheng (2019).

higher scores can be generated with a higher probability of satisfying any personal design taste, but what is more important, that ML can learn relationships that may be difficult to articulate in human parlance. It should be noted that, given the natural difficulties human designers face when asked to score many forms consistently to the same standard. In these cases, the scores were mapped into a grading scale, from A to D, which considers the number of times the forms have been selected. This explains the final selection presented in **Figure 5** where a structure with an initial score of 0.729 is chosen on top of another with a score of 0.864. This is a compromised solution, but one that massively narrows down the variety of forms from which the designer has to choose. Thus, the door is open to integrate both mechanistic and quantifiable metrics with other kinds of design considerations and to apply this to a diversity of design tasks.

## 4 AI APPLIED TO THE DESIGN OF BUILDING STRUCTURES

The rationalization of the design process of building structures, within a structural optimization framework, has usually been separated into three components (Havelia, 2016): 1) topology, which involves decisions on the number and connectivity of members, usually done without optimizing the connection itself; 2) shape, which involves decisions related to the location of elements and the layout of joints; and 3) sizing, which involves defining member cross sections. More often than not, these components are treated separately in the scientific literature, however, they are strongly interrelated and decisions involving one will greatly affect the others. Usually, the layout space is reduced by architectural considerations, but it will still encompass a large number of potential locations that are difficult to explore without any pre-determining guiding principle. Besides, early estimates of the building cost are usually based on weight, however, the majority of the total cost can sometimes be attributed to fabrication and erection which are not always directly proportional to weight (Kang and Miranda, 2005) In addition, material costs depend not only on tonnage, but also on the type and size of cross sections utilized and erection costs are also highly contingent on geography and local market conditions Klanšek and Kravanja (2006). These facts will automatically render impractical most topology optimization studies carried out to date.

Some studies have incorporated, albeit in a simplified manner, the design complexities outlined above. For example, Torii et al. (2016) developed an optimization algorithm that penalizes the number of members and joints in the structure in proportion to the number of connected elements. Unfortunately, this was only applied to trusses and no consideration was given to the fact that the connection type is determinant in their cost. Hassett and Putkey (2002) collected a comprehensive list of cost drivers and their values for the most common moment-resisting and pinned connections in the AISC catalogue. And Zhu et al. (2014) considered constructibility issues in the optimization of frames and demonstrated that some structures with a less efficient load path can improve constructibility and lead to overall lower costs. Zolfagharian and Irizarry (2017) used Principal Component Analysis, a clustering ML technique, to group constructibility factors into six major categories. To this end, they assembled a dataset, via industry interviews, on 79 different constructibility factors with given scores. As the design space increases exponentially with the number of structural elements, the number of structural typologies analysed, their connectivity and the constructibility considerations, most currently available optimization methods are rendered impractical for full-scale real implementation. Other proposals, like that of Havelia (2016) have used methods based on topology and sizing optimization within a multi-disciplinary architecture suitable for 2D steel framed buildings. Again, Havelia's study showed that a heavier structure can be more economical than its lighter counterpart when connection and fabrication costs are taken into account. One drawback of this study is that serviceability constraints like maximum deflection or vibrations are not considered and therefore its applicability to real designs is hampered. On the other hand, high profile applications of structural optimization like the Chicago 800

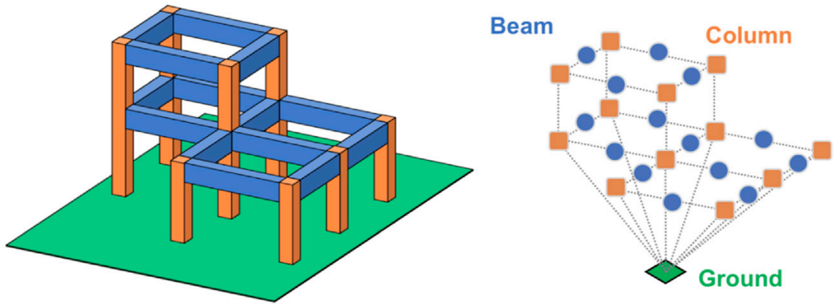


**FIGURE 6 |** An example building structure and its structural graph representation suitable for analysis by GNN, from Chang and Cheng (2020).

West Fulton Market or Shezhen's Financial Center do not aim to optimize the whole building economy or constructibility but are concerned with only a small proportion of its load carrying elements.

One of the first studies that departs from the above mentioned trend is that of Ranalli (2021) who proposed a new AI-based optimization module for the design of a flooring system with varying degrees of composite action. User-defined variables employed include the depth of the slab, the height of the steel deck, the properties of concrete, a range of possible cambers, the option to use shoring during construction, the degree of composite action, and the range of wide flange sections. The optimization framework iterates through each beam and girder, automatically determines its static scheme, computes the governing moment and deflection demands under the applied loads, and efficiently iterates through the set of available design options to find the most economical and feasible solution. Serviceability limits are considered and material and labour rates are assigned to arrive to an optimal solution through a scenario exploration. However, the gravity resisting columns are not considered, nor are issues related to their continuity and the rotational restraint (or flexibility) they provide to the floor. Nevertheless, the main strengths of Ranalli's AI-driven optimization framework are its computational scalability and its readiness of applicability to new steel frame designs with minimal pre-processing efforts.

Another interesting work was performed by Chang and Cheng (2020) who re-formulate building frames as graphs (**Figure 6**)and use Graph NN (or GNN) trained on simulation results that can learn to suggest optimal beam and column cross-sections. This is one of the first attempts to use GNN in the realm of design optimization aided by differentiable approximators. The optimization objective employed by Chang and Cheng (2020) is simplistic, involving only mass minimization, but a variety of constraints is considered together with serviceability limits to produce optimal designs. The results are reported to be consistent with typical engineering designs and also comparable to outputs from Genetic Algorithm optimizations. The main limitations of this work are related to the absence of slab continuity effects and the treatment of the building skeleton as an input. However, the possibility of implementing a graph representation and generation algorithm in the initial phases of design to provide an end-do-end solution generating tool is worth exploring further.

Similarly, Ampanavos et al. (2021) developed a ML system for the automatic generation of building layouts aimed at helping architects present structurally feasible solutions during the early stages of the project. A peculiarity of the system is that it does not aim to estimate the full structure to start with, but uses an iterative approach where the neural network gradually extends the solution as necessary. In this way, the NN has better changes of identifying patterns on a small building area at each step. However, this approach is also prone to error accumulation for large structures, although this error is dependent on the size of the training dataset. Besides, the column positioning can be noisy. However, future combinations of this approach with element sizing tools and more sound structural considerations are likely to produce a scalable and helpful methodology.

In his thesis, Ranalli (2021), mentioned above, also considered the problem of sizing lateral load resisting systems against strong loads typical of earthquakes. The author treated this problem in two iterative phases, the first of which searches for the most economical solution that meets strength, constructibility and ductility criteria. The second phase checks for lateral drift compliance and design load combinations. An energy based analysis is performed in case particular floors need to be adapted to comply with the drift limits. The strength of this study is that is able to combine commonly used analysis tools and relatively justified cost functions to provide a whole-encompassing approach to building design. It is also worth noting that a high variance of cost across different design scenarios was observed highlighting the important role of even small changes in the variables on the overall building cost.

The above mentioned studies are mainly devoted to steel framed solutions, where the domain is discrete since only a certain number of steel sections are available. This may simplify and reduce the design space and facilitate the consideration of constructibility functions. By contrast, designing concrete structures may introduce additional complications since a relatively broader design space is to be considered with added variations in member detailing. These issues were approached by Pizarro and Massone (2021) who aimed at supporting the design of reinforced concrete buildings by keeping track of previously accepted design solutions, in

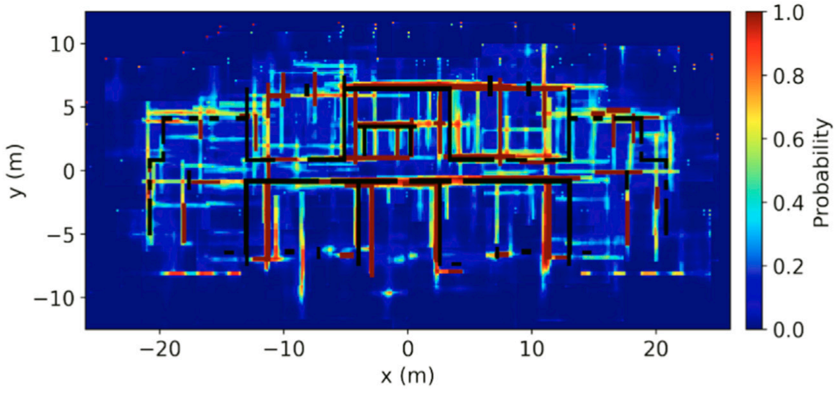


**FIGURE 7 |** Predicted plan obtained by Pizarro et al. (2021).

contrast with other topology optimization methods based on more heuristic approaches like those proposed by Zhang and Mueller (2017), which do not have this feature.

Pizarro and Massone (2021) proposed a predictive model for the length and thickness of reinforced concrete building walls based on Deep NN trained with 165 Chilean residential projects. The walls were described in both geometrical and topological domains and three variations of the data, achieved by modifying the building plan angle and its scale, were considered. Highly accurate predictions of wall thickness and length were obtained and the authors recommend the method to provide the engineer with a preliminary but reliable wall plan. Although not holistic in its scope, this work stresses the potential of ML-based tools to enhance the engineer-architect interaction via the machine. Besides, although important in number, the database of 165 building designs employed puts in evidence the small-data nature of most structural engineering problems. In addition, the regressive model proposed by Pizarro and Massone (2021) does not incorporate contextual information and can lead to poor estimations of wall translation.

In a companion paper, Pizarro et al. (2021) improve upon their previous work and present Convolutional NN models that take the architectural data as input and can output the final engineering floor plan. To this end, two regressive models are used to predict the thickness, length, and translations of the wall. A second prediction of plan is obtained by using a model that generates a likely image of each wall. Both independently predicted plans are combined to lead to the final engineering design as shown in **Figure 7**. This methodology was proven to be a feasible option to accelerate decisions regarding the building layout and can be adapted to incorporate estimations of building drift demands or force distributions.

Along the same vein as the above-mentioned studies, the work of Liao et al. (2021) uses generative adversarial networks (GAN), that have been previously used to generate building floor plans (Chaillou, 2020), to perform structural designs of shear wall residential buildings. To this end, the authors use a semantic process to extract essential architectural and structural features from technical drawings of around 250 pairs of architectural-structural human designs. The outputs of the GAN model are evaluated in two case studies where their safety and economy are compared against designs carried out by competent human engineers. It is concluded that GAN-generated designs can improve significantly the speed at which new designs are generated without compromising the quality of building structures. Similarly, Lou et al. (2021) optimized the shear wall layout of high-rise buildings through a tabu search algorithm. Support vector machines (SVM) were used to construct surrogate models and speed-up the analysis time. Their objective was to minimize the structural weight with constraints on the period ratio and story drift. Through a series of case studies, the authors showed that the proposed approach works well. In this case, however, a meta-heuristic algorithm was used for the optimization part and the ML model was employed only to reduce the computational cost due to repetitive structural analyses.

## 5 THE GRAILS OF CREATIVITY AND INTUITION

Modelling human intelligence on the perceived way we process and understand information has lead to remarkable tools that can augment the engineers' design skills, allowing them to operate over large datasets and make ever more accurate predictions of response and performance. However, understanding and reasoning are not the only, or even the most frequent, ways engineers use to solve problems (Graziano and Leone, 2019). Intuition, understood as "a form of recognition" (Simon, 1995), or the ability to understand something almost instinctively without concious reasoning, plays an important role in engineering decisions. In fact, engineers, who may prefer to call it judgement, use intuition even when developing computer models such as when framing the design question the model is set to answer or deciding what to include and what to leave out of that question. Appeals to recognize the importance of intuition in engineering design have grown almost in parallel with the proliferation of computational tools in engineering (Young, 2018).

Recent pioneering research has started to look at ways to integrate intuition into AI and ML with encouraging results in areas as diverse as chemical engineering (Duros et al., 2019), automated planning (Kim et al., 2017), and mathematics (Davies et al., 2021). In all these cases, the authors propose schemes for the incorporation of a human experimenter as part of the solution-generation process. For example, Davies et al. (2021) approach is akin to a "test bed for intuition" where ML algorithms guide the experimenter by: 1) verifying the existence of a hypothesized mathematical pattern using supervised ML; and 2) if the pattern exists, by helping in understanding it using Attribution Techniques. Likewise, Duros et al. (2019) propose the integration of human and machine in the selection of potential chemical experiments within a single decision-making loop. In all these cases, by making human and machine work together, a significantly higher performance is achieved than either of them could achieve individually.

In the structural engineering field, a relatively similar approach has been attempted by Danhaive and Mueller (2021). In their work, briefly described in the previous section, Danhaive and Mueller allow the design engineer access to a family of 2D latent spaces that can be adapted by changing the user-defined performance condition. This feature encourages designers to investigate different trade-offs between performance and other design features and opens the door for a more integrated machine-designer collaboration that does not aim to replace intuition with deterministic and quantitative rules but instead to incorporate it within the design process. However, to make the latent space intuitive and apt for human exploration, Danhaive and Mueller have to limit it to two dimensions. This highlights a defining feature of human intuition: that it emerges from the natural inability of the human mind to process scenarios with multiple variables (Halford et al., 2005). It is when faced with high uncertainties and multiple unknowns that the engineer resorts to intuition to be able to define a direction of exploration without getting boggled by the details. One would expect that the growing ability of AI to identify complex patterns in high-dimensional spaces will supersede the advantages of rules of thumb and educated guesses in determining high level features of the design process. Until then, the integration of human and machine intelligence offers a promising alternative. In addition, intuition's deciding role during the initial design stages fades down as the design is gradually informed by mechanics and structural analyses. Nevertheless, intuition remains as one of the last strongholds of traditional structural engineering practice as it adapts and responds to the challenges of digitalization. The other being creativity.

Creativity is usually defined as the generation of novel and useful ideas (Jung et al., 2013). This immediately invokes the existence of a judge, a person to whom the idea, or in our case the design, would appear novel or useful. It is perhaps this subjective strength of the term the reason for its recent prominence in the discussions around the training of the next generation of structural engineers (Ibell, 2015) where it is usually pitted against the more quantifiable (and declining) numerical skills. However, this subjectivity is not amorphous or ethereal since creativity does not emerge in the vacuum but is rather tied to socially contextualized phenomena (Kaufman and Sternberg, 2010). As such it will appear that creativity can be taught and learnt, if by humans also by machines. In this regard, the examples presented in previous sections have highlighted the possibility of incorporating measures of taste in ML tools and algorithms have been shown to enhance the diversity of the solutions found. In this context, it has been argued that novelty constitutes a critical issue to address with computational approaches, e.g., (Amabile, 2020). This is due to the fact that training of ML models usually relies on minimizing a loss expectation function and therefore the model is encouraged to perform well in the most common elements of already established knowledge.

A number of approaches could be taken to improve the "creativity" of ML algorithms (Boden, 1998), namely: 1) by producing novel designs from the combination of familiar solutions, 2) by discovering new paths in conceptual spaces, and 3) by disrupting the design space with solutions that were not previously considered. Consequently, it would seem that there are yet many routes to encourage artificial creativity. These aspects are in fact being developed within (and are probably more suited to) reinforcement learning approaches. Similarly, efforts to incorporate heuristic thinking into AI have been trialled in other branches of design (Nanda and Koder, 2010) and it may be beneficial to explore those in structural engineering also. At the end of the day, heuristics (intuition) is already routinely used by engineers to reduce the search space of potentially feasible designs, e.g., (Maqdah et al., 2021; Palmeri et al., 2021; Danhaive and Mueller, 2021). A perceived hurdle, however, comes form the fact that much of the progress of ML and AI has come from the formalization of mathematical and logical approaches aiming at well defined problems with clear goals. To answer this, may be the distinction between: 1) algorithms that search the entire decision space, and 2) those that perform bounded searches to provide satisfactory solutions (Simon, 2019) can be helpful here. Ultimately, much to the regret of the new breed of curriculum transformation proposers, computer programs constitute a body of empirical phenomena to which the student of design can address himself and which he can seek to understand. There is no question, since these programs exist, of the design process hiding behind the cloak of "judgment" or "experience" (Simon, 2019). To which we may add:" or creativity".

None of the above mentioned explorations to embed artificial intuition or to enhance artificial creativity in machine intelligence has yet been fully explored in structural engineering design. This constitutes an area of great research potential. Since much of the ML research has been based on mimicking the theories of human cognition it is entirely possible that the restrictions of human creativity and intuition are in turn limiting machine intelligence. This calls for a re-evaluation of the human-machine creative partnership. New investigations that take at face value the human-machine duo, like it has been done in other creative industries (Nika and Bresson, 2021), are likely to benefit the realm of structural design with fresh and surprising views. So it seems that in the short term we may be seeing more design cooperation between human and machine where the role of ML, however, is not circumscribed to repetitive tasks but can assist in the creative work itself.

## 6 CONCLUSION

It has been suggested (Gero, 1994) that there are three views that can be taken about artificial intelligence in design: 1) AI as a framework in which to explore ideas about design; 2) AI as provider of a schema to model human design; and 3) AI as a means to allow the development of tools for human designers. This review paper has concerned itself with a strong version of the third view, by highlighting the path not only towards the development and proliferation of ML tools but also towards the automation of entire parts of the design process. In fact, a multitude of ML tools have been proposed aimed at different individual tasks along the design chain (like predicting the strength or condition of a given element, or the optimization of a section or connection). Design, however, is more complex than any of these individual tasks and ML methods aimed at it are more scarce.

It has been shown that ML tools have now started to appear that allow engineers to access complex multi-dimensional spaces beyond the ability of human intelligence alone. It was argued that the defining characteristic of ML to identify complex patterns and use those to predict or propose new engineering design solutions will form the basis for the automatization of increasingly large portions of the design endeavour. Importantly, these ML-enabled explorations can include not only hard mechanistic constraints but also metrics of taste and intuition. Indeed, although currently still producing timid results, the learning capacity of ML algorithms can be used to incorporate aesthetic and creative criteria that is sometimes difficult to articulate but which nevertheless the machine can learn. In addition, this learning can feed not only from engineering precedents at large but from the "best" precedents we currently have.

Another advantage of ML algorithms applied to design is found in the increased diversity of outputs produced. ML algorithms have been shown to increase the design diversity by recombining the features that characterise individual designs producing solutions beyond those which would have been imagined by human engineers. This recombination is usually neglected in engineering designs due to the large demands of data and time associated with it. However, with the use of data augmentation tools and computer simulation, it is expected that this hurdle will be solved sooner rather than later.

Nonetheless, the data requirements of ML algorithms will continue to be a limiting factor, particularly in the structural engineering field. If the ML-enabled design automation is to be attained, larger datasets of real-world designs should be made freely available. Most of the ML algorithms reviewed herein have used training datasets in the order of the hundreds. This is "small data" science and requires specific data augmentation techniques that the focus on "big data" is currently concealing. Data acquisition and curation is indeed the single most important step in the development of ML models. Robust, complete and reliable data sources should be produced and shared. Echoing current public demands in the sustainability and industrial ecology quarters of the design enterprise (in terms of environmental impact, LCA, etc.) (D'Amico et al., 2019) the field of structural ML design also needs all its stakeholders to contribute their design databases. Only then, truly optimal and "out of the box" ML-enabled design solutions can be realistically proposed paving the way towards more resilient, economical and sustainable new structures.

All in all, we should continue to guard against the well known dangers lurking around ML implementation. To this end, issues of interpretability and overfitting should continue to be raised and efforts made to increase model explainability (by conducting and reporting sensitivity tests and marginal effects studies for example), increase data sources, improve noise filtering processes and carefully select the ML models (to reduce overfitting) should carry on. Finally, it has been said that ML tremendous success so far has been achieved by showing that some cognitive processes thought to be complex and difficult are, in fact, not so. This, taken together with the acceptance that routine design is broadly defined as that activity that occurs when all the necessary knowledge is available (Gero, 1994); should prepare us well to be less surprised when the next generation of ML tools hits the structural design enterprise with the automation of large portions of the design process. Hence the question of how long until, not if, the human engineer is superseded in structural design.

## AUTHOR CONTRIBUTIONS

CM-C contributed to conception and design of the study, it organisation, wrote the paper, read and revised it.

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