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Human-in-the-Loop Structural Optimization: A Paradigm Shift in Structural and Architectural Design

Jonathan MELCHIORRE[*,a], Amedeo MANUELLO BERTETTO[a], Giuseppe C. MARANO[a], Sigrid ADRIAENSSENS[b]

[*,a] Politecnico di Torino, DISEG, Department of Structural, Geotechnical and Building Engineering
Corso Duca Degli Abruzzi, 24, Turin, 10129, Italy
jonathan.melchiorre@polito.it

[b] Department of Civil and Environmental Engineering, E208 Engineering Quadrangle, Princeton, New Jersey - 08544, USA.

Abstract

The construction industry (CI) is a significant contributor to environmental impact, constituting a substantial portion of the human ecological footprint. In this context, the implementation of structural optimization paradigms in the usual practice can be a pivotal factor in reducing the impact of the CI. In traditional practice, the optimization problem inherently demands a mathematical formulation. In this perspective, integrating the designer's creative vision into the optimization process is challenging due to the inherent difficulties of mathematically and objectively formalising their sensitivity and creativity. The contemporary challenge lies in transcending this limited conception and embracing a more integrated approach. This study proposes a Human-In-The-Loop structural optimization approach, leveraging the synergy between artificial intelligence and human intuition. This paper introduce a perspective change that aims to establish a symbiotic relationship where the designer's creative vision guides the optimization algorithm. This dynamic interaction between humans and machines fosters a convergence toward solutions that are not only structurally optimal but also architecturally innovative. By formulating a multi-objective optimization problem and dynamically integrating designer preferences, the proposed approach aims to find a harmonious balance between architectural form and advanced structural performance. The use of advanced machine learning algorithms enables the system to adapt and learn from the designer's preferences over time. In this way, the algorithm is guided by the designer's sensitivity, aiming to converge on a solution that is optimal from both architectural and structural perspectives. This research establishes a new paradigm for structural optimization by leveraging the integration of human and artificial intelligence. This integration seeks to incorporate human creativity into structural optimization processes, aiming to develop structural projects that achieve dual sustainability objectives, both economically and environmentally.

Keywords: Artificial Intelligence, Structural Optimization, Creative Vision, Architectural Design, Human-AI Integration.

1. Introduction

The construction industry (CI) holds significant responsibility for environmental impact, making up a considerable portion of the human ecological footprint. CI is a major emitter of greenhouse gases (GHGs), accounting for about 30% of global emissions [1]. Moreover, it consumes a huge amount of raw materials, constituting half of the world's total consumption, and is responsible for 40% of global energy use [2]. These activities contribute to pollution in approximately 40% of potable water sources, posing serious threats to both ecosystems and human health [3].

In addition to its environmental impacts, CI generates substantial waste, with construction and demolition activities alone accounting for 50% of landfill waste globally. Furthermore, the industry is a significant contributor to air pollution, responsible for 23% of global air pollution levels. These environmental challenges not only degrade natural ecosystems but also impose significant public health risks and exacerbate climate change.

Despite these environmental concerns, the construction sector remains a cornerstone of the global economy, contributing approximately 10% to the world Gross Domestic Product (GDP), amounting to a staggering 7.5 trillion USD. Indeed, within the European Union (EU), the construction industry (CI) serves as a significant economic driver, supporting approximately 18 million direct jobs and contributing around 9% to the region's Gross Domestic Product (GDP) [4].

However, with the projected global population growth and the rising affluence in emerging economies, the demand for infrastructure and buildings is expected to increase. It is estimated that global building floor area could double by 2050 [5], further intensifying the environmental footprint of the construction industry.

Given the importance of the construction industry from both environmental and economic perspectives, even slight improvements in this sector can yield substantial benefits with far-reaching global impacts.

In this context, integrating structural optimization paradigms into standard practice can prove pivotal, offering substantial benefits in both the short and long term. By considering projections up to 2050, the potential impact of structural optimization in the CI becomes even more evident. Implementing such optimization techniques could result in a substantial reduction in annual material demand for building construction. Specifically, estimates suggest a decrease of over 95 million metric tons of concrete and more than 3,000 million kilograms of steel. This reduction would translate into significant energy savings, amounting to more than 100 trillion BTU per year, and an annual decrease in GHG emissions by more than 10 million metric tons of CO_2 equivalent [5].

Indeed, in recent years, there has been a significant surge in research efforts dedicated to advancing structural optimization techniques [6]. Notably, the great majority of these studies focus on three key objectives: minimizing costs [7], enhancing structural performance [8], and mitigating the environmental impact of structures.

Furthermore, architectural design optimization projects have emerged over the years [9], albeit in limited numbers. These initiatives are primarily focused on optimizing building energy consumption, refining floorplan layouts, maximizing daylight in enclosed spaces [10], minimizing bracing elements [11], and rationalizing the panelization of curved surfaces.

With the rise of computational tools, digital methods have become invaluable for designers in evaluating both quantitative and qualitative performance. Traditional optimization practices typically involve mathematically formulated objectives and constraints. While there are numerous optimization algorithms available, the majority require a quantitative objective function. As a result, while optimization techniques can effectively address certain conceptual design requirements, they may not be suitable for addressing unquantifiable but yet significant objectives.

In this context, incorporating the designer's creative vision into the optimization process presents challenges, primarily due to the inherent complexity of quantifying sensitivity and creativity mathematically and objectively. Typically, architectural design is established separately before tackling the optimization problem, following a decoupled approach. Consequently, it is then used to establish geometric constraints within the problem. This approach often results in a solution that represents a suboptimal configuration from both structural and architectural perspectives.

The contemporary challenge is to surpass this constrained view and adopt a more integrated approach, where the designer's creative vision seamlessly merges with the optimization project. In this advanced paradigm, architectural design shifts from being a mere constraint to an active collaborator in shaping the objectives of structural optimization.

The aim of this article is to propose a methodology for integrating the designer's creative vision into structural optimization protocols by leveraging on interactive optimisation algorithms and machine learning. This research proposes a human-in-the-loop structural optimization approach to explore this paradigm shift. The Human-In-The-Loop protocol entails leveraging human feedback to guide the optimization process. This methodology has been successfully developed and deployed in domains such as exoskeletons [12] and robotic prosthetics [13] to enhance the integration of these devices with the human user. In structural optimization, an initial endeavour to formulate a similar protocol was explored in [14] and [15].

In this research, the idea is to present a methodology to leverage on an interaction between artificial intelligence algorithms and the designer with the goal of guiding the optimization process through the designer's intuition and creative vision. This establishes a symbiotic relationship between artificial intelligence and human creativity, allowing the architectural principles to become optimization objectives. The objective is to incorporate the designer's choices directly into the optimization algorithm loop. Thus, the algorithm is influenced by the designer's sensitivity, aiming to reach a solution that is optimal both architecturally and structurally.

Practically, this involves formulating a multi-objective optimization problem where one of the objectives is the adherence to dynamically defined architectural and functional design principles set by the designer. This is achieved by dynamically incorporating the designer's preferences into a multi-objective evolutionary optimization algorithm [16]. The preferences shape the generation of solutions, steering the optimization process. By utilizing advanced machine learning and artificial intelligence algorithms, the system can learn from the designer's preferences and intentions over time. The method entails identifying the parameters that significantly impact the designer's decisions and eventually clustering proposed solutions based on the designer's interaction.

This protocol aims to define a paradigm shift in structural optimization by harnessing the synergy between human intuition and artificial intelligence. By integrating human creativity into structural optimization processes, the goal is to develop structural projects that not only excel in economic and environmental sustainability but also are interconnected with architectural creativity.

2. Methodology

In this section, the methodology for developing the Human-In-The-Loop protocol for structural optimization is defined.

Firstly, the definition of the multi-objective optimization problem and the concept of Pareto sets are revisited.

Secondly, the elaboration on how the Human-In-The-Loop protocol facilitates the integration of the designer's creative vision into the optimization process is provided.

Finally, a method based on machine learning algorithms is introduced to create models that learn from the designer's evaluations, ensuring accurate assessment of the adherence of various structural solutions to the designer's creative vision.

2.1. Structural optimization problem definition

Multi-objective optimization problems, often encountered in engineering and decision-making contexts, involve the simultaneous consideration of multiple conflicting objectives [17]. These objectives may represent different aspects of a system's performance or different stakeholder preferences. The challenge lies in finding solutions that achieve a balance among these objectives, as optimizing one may come at the expense of another. The problem can be generally defined as follows:

$$\begin{aligned} &\textit{Find } \vec{x} = [x_1, ..., x_n]^T \in \Omega \subseteq \mathbb{R}^n \textit{ such that} \\ &\qquad \min_{\vec{x}} \vec{f}(\vec{x}), \quad \text{with } \vec{f}(\vec{x}) \in \mathbb{R}^m \\ &\text{s.t.} \quad g_q(\vec{x}) \leq 0 \qquad \forall q = 1, ..., n_q, \\ &\qquad h_r(\vec{x}) = 0 \qquad \forall r = 1, ..., n_r, \end{aligned} \tag{1}$$

Here, the design variables vector $\vec{x}$ comprises n dimensions, each subject to box constraints $x_i^l \leq x_i \leq x_i^u$, commonly referred to as side constraints. Additionally, the objective functions vector $\vec{f}(\vec{x}) = [f_1(\vec{x}), ..., f_m(\vec{x})]^T$ consists of m components.

In the problem formulation, the inequality constraints $g_q(\vec{x}) \leq 0$ represent restrictions that must be satisfied for all $q = 1, ..., n_q$, where n_q denotes the total number of inequality constraints. Conversely, the equality constraints $h_r(\vec{x}) = 0$ ensure that specific conditions are met for all $r = 1, ..., n_r$ with n_r denoting the total number of equality constraints.

In real-world problems, the objective functions (OFs) often represent contrasting aims that cannot be minimized simultaneously. As a result, the optimal solution in multi-objective optimization problems may not be well-defined. When considering all the objective functions together, no solution may be better than others, but optimality is reached through a trade-off. To evaluate the quality of a particular solution, it is necessary to assess the objective functions. In a multi-objective optimization problem, the feasible set is only partially ordered, and it is not possible to unequivocally compare two potential solutions.

To evaluate the quality of solutions, the *Pareto order theory* for a minimization problem is adopted. Given two output vectors $\vec{u} \in \mathbb{R}^m$ and $\vec{v} \in \mathbb{R}^m$, it is said that $\vec{u}$ *Pareto dominates* $\vec{v}$ ($\vec{u} \prec \vec{v}$) if:

$$\begin{aligned} u_i \leq v_i, \quad \forall i = 1, 2, ..., m \\ u_j < v_j, \quad \exists j = 1, 2, ..., m \end{aligned} \tag{2}$$

Thus, a vector $\tilde{\vec{x}}$ is called *Pareto optimal* if and only if there exists no other vector $\vec{x}$, such that $\vec{v} \in \mathbb{R}^m$, and $\vec{v} = F(\vec{x}) = [f_1(\vec{x}), ..., f_m(\vec{x})]$, dominates $\vec{u} \in \mathbb{R}^m$, where $\vec{u} = F(\tilde{\vec{x}}) = [f_1(\tilde{\vec{x}}), ..., f_m(\tilde{\vec{x}})]$.

The Pareto optimal solution is one where there is no other feasible solution that can improve on some objective functions without worsening at least one other objective function. The Pareto optimal set comprises all output vectors of these Pareto optimal points, also known as *non-dominated solutions*, in the objective space and can be defined as in 3.

$$\mathbf{P} = \{\tilde{\vec{x}} \in \Omega \textit{ such that } \nexists \vec{x},\ F(\vec{x}) \preceq F(\tilde{\vec{x}})\}, \tag{3}$$

Thus, the Pareto front is represented as:

$$\mathbf{P_F} = \{\vec{u} = F(\vec{x}) \textit{ with } \vec{x} \in \mathbf{P}\}. \tag{4}$$

Equation 2 clearly illustrates that establishing the set of optimal solutions, and thus the Pareto front, requires a quantitative definition of the objective functions. Indeed, to identify non-dominated solutions, it is essential to assess them in quantitative terms.

2.2. Human-In-The-Loop protocol

In this context, the Human-In-The-Loop protocol seeks to integrate the designer's perspective into the objective functions to be optimized. Leveraging the inherent mechanisms of evolutionary multiobjective optimization algorithms, quantifying the architectural appeal of specific solutions could naturally guide the evolution of optimized structures towards designs most aligned with the designer's vision.

Indeed, quantifying the designer's creative vision in mathematical terms poses a significant challenge. Even when the designer has a clear structural design vision, given two different solutions, it is very difficult to define a function to identify which of the two solutions is closer to the designer's preference.

From the designer's perspective, however, expressing a preference between the two solutions is straightforward. Hence, the aim of the Human-In-The-Loop approach is to incorporate the designer into the optimization cycle. In doing so, the designer becomes the evaluator, judging the work based on their aesthetic criteria.

Therefore, the idea is as represented in the workflow depicted in Figure 1. As in typical structural optimization problems, it is necessary to start with a parametric definition of the structure. In this way, different structural solutions can be defined as the parameters change. The definition of the optimal combination of parameters involves using an evolutionary optimization algorithm such as the Non-Dominated Sorting Genetic Algorithm (NSGA II) defined by Deb et al. [16].

It would seem the case that the employment of evolutionary optimization algorithms, particularly Interactive Optimization Algorithms [18], has showcased the potential to guide the optimization process according to user choices made during optimization. Studies such as [14] and [15] have successfully illustrated the feasibility of this approach in structural optimization.

Considering as an example the NSGA II, in the initial phase, the algorithm generates a population of potential solutions by creating semi-random combinations of design variables, which define various structural solutions. Subsequently, it assesses whether these generated solutions satisfy the imposed constraints. Those solutions meeting the constraints are then evaluated based on the different objective functions.

In this phase, the Human-In-The-Loop process entails presenting the solutions to the designer for evaluation, where they assign a grade reflecting their aesthetic preferences. This grade quantifies how closely the proposed solutions align with the designer's vision. Each solution is consequently linked to a numerical evaluation corresponding to one of the objective functions. Utilizing this assessment, it is then possible to employ Equations 2 to determine which solutions are non-dominated. During this phase, a non-dominated sorting approach [19] is implemented on the solutions, considering all the objective functions. As a result, the solutions are sorted by both considering the objectives in terms of costs, whether economic or environmental, and in terms of adherence to the designer's vision.

Once the solution set undergoes sorting, the genetic algorithm combines the top solutions to create a new population. The iteration of this process allows the algorithm to learn from the previous solutions, continually generating improved alternatives until it converges to the Pareto set, as defined in Equation 3.

The Pareto set encompasses all solutions that offer the optimal compromise between cost functions and the designer's preferences. This empowers the designer to select, from a pool of optimal solutions, the one that most accurately aligns with the specific design requirements.

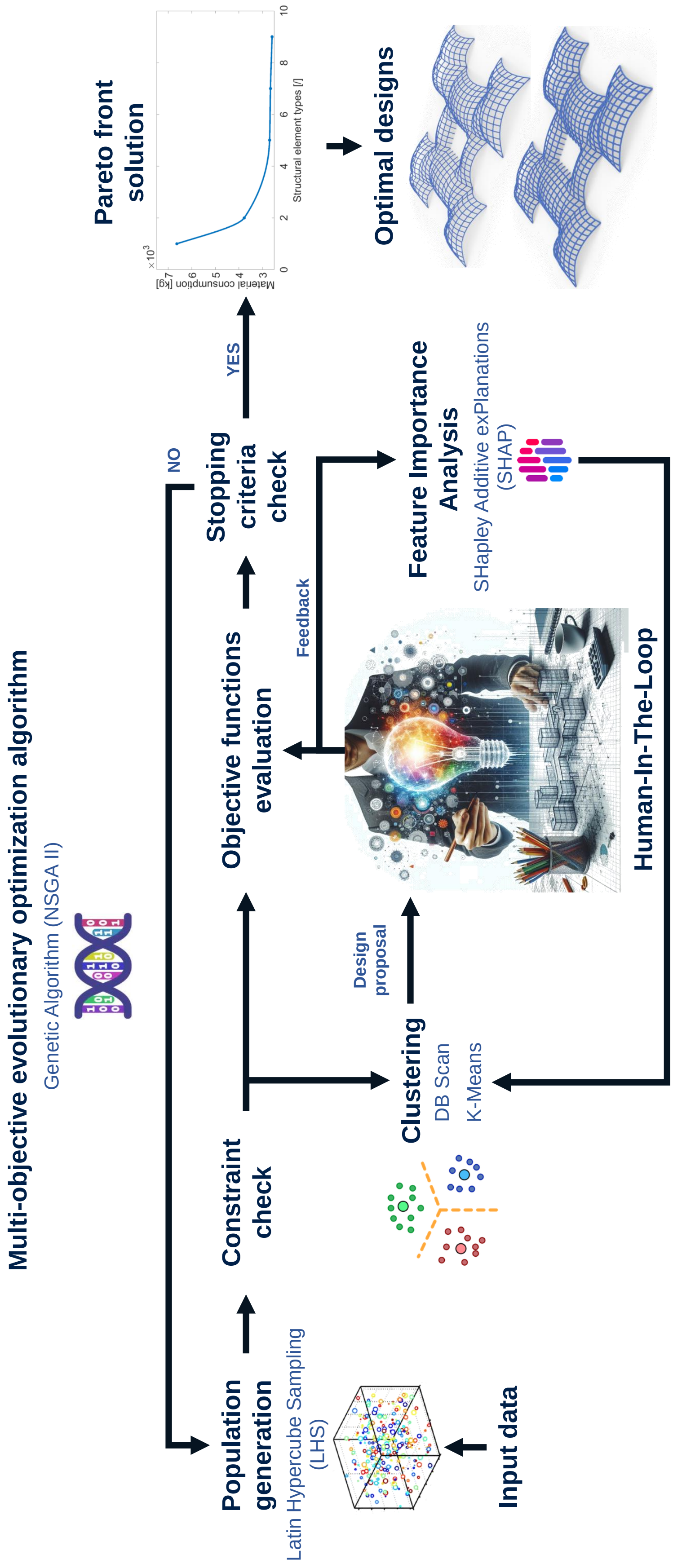

Figure 1: Human-In-The-Loop workflow.

2.3. "Machine" Learning the designer's creative vision

In the previous section, the Human-In-The-Loop protocol was introduced, integrating the designer's evaluation into the optimization process. This approach allows the designer's vision to influence the generation of optimal solutions that align with their creative preferences. However, a potential drawback of this method is the vast number of solutions typically generated during optimization. This can result in tens of thousands of potential solutions, posing a challenge for the designer who would need to evaluate each one, rendering the method impractical.

Therefore, this section presents a method for leveraging machine learning algorithms to develop models capable of learning the designer's preferences. This approach aims to automate the evaluation process, alleviating the burden of manually assessing a large number of potential solutions.

The proposed approach involves employing a combination of Feature Importance Analysis [20] and clustering algorithms [21] to categorize solutions according to the parameters that exert the most significant influence on the designer's evaluation.

Once the initial population of potential solutions is generated, an unsupervised clustering technique [22, 23] will be employed to categorize individuals within the population based on their design variable values.

Subsequently, only a select few individuals from each cluster will be presented to the designer for evaluation, rather than the entire set of solutions. Each cluster will then be assigned a rating derived from the average ratings of its constituent individuals. The evaluation of each individual within a cluster will be determined based on the rating assigned to the cluster as a whole. This approach allows the algorithm to automatically evaluate individuals within the same cluster, sparing the need for manual evaluation by the designer.

To enhance the precision of the approach, Feature Importance Analysis is employed to identify the design variables that exert the most significant influence on the designer's evaluation. This analysis will be conducted using techniques such as permutation feature importance [24] and the Shapley additive explanations (SHAP) method [25].

Following the designer's ratings and the outcomes of the Feature Importance Analysis, a supervised clustering algorithm can be trained to classify the generated solutions. This secondary clustering algorithm will focus solely on the design variables identified as having the most significant impact on the designer's evaluation by the Feature Importance Analysis. This tailored approach is necessary because not all design parameters typically influence the aesthetic qualities of the structure.

For each population generated by the optimization algorithm, the process will be iterated by incorporating the newly evaluated individuals into the training dataset for both the clustering algorithm and Feature Importance Analysis. Through these iterations, the accuracy of the algorithms for clustering individuals improves gradually. Ultimately, this iterative approach aims to achieve a level of accuracy where the evaluation of solutions can be fully automated, eliminating the need for designer intervention.

3. Conclusions

In conclusion, this study has presented a novel approach to structural optimization that allows to integrate the designer's creative vision into the optimization process. By leveraging the Human-In-The-Loop protocol, designers can actively participate in defining the optimization objectives, leading to the generation of solutions that align more closely with their aesthetic preferences.

The proposed methodology involves the use of evolutionary optimization algorithms, such as the Non-Dominated Sorting Genetic Algorithm (NSGA II), to generate a population of potential solutions. These solutions are then subjected to evaluation by the designer, who provides ratings based on their adherence to non-objective aesthetic criteria.

To address the challenge of scalability when dealing with a large number of potential solutions, machine learning algorithms are employed to automate the evaluation process. Feature Importance Analysis, along with clustering algorithms, enables the identification of design variables that have the greatest influence on the designer's evaluation. This allows for the prioritization of solutions for manual evaluation, reducing the burden on the designer.

By iteratively refining the clustering algorithms and Feature Importance Analysis based on the designer's evaluations, the method aims to achieve a level of automation where solutions can be evaluated fully automatically. This iterative process enhances the accuracy of the algorithms and streamlines the optimization workflow. Overall, the proposed methodology aims to generate structural solutions that not only meet functional requirements but also satisfy the designer's aesthetic preferences. In view of the fact that the algorithm is designed to incorporate the designer's creative vision within the structural optimisation protocol, and recognising that this vision is inherently subjective, it is essential to involve different subjects in the tests in order to assess how their subjectivity influences the optimisation results. However, the objective of this article is to introduce the methodology and the new protocol for approaching structural optimization. Consequently, presenting the test results is beyond the scope of this manuscript.

Future developments of the method will include extensive tests on different designers to assess how their subjectivity may influence the results obtained during the optimisation process. Finally, future research directions may involve further refinement of the automated evaluation process and the application of the methodology to a broad range of structural design problems.

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Author(s): Jonathan Melchiorre[1*], Amedeo Manuello Bertetto[1], Giuseppe Carlo Marano[1], Sigrid Adriaenssens[2]

Affiliation(s): [1*]Politecnico di Torino, DISEG, Department of Structural, Geotechnical and Building Engineering.

[2]Princeton University, Department of Civil and Environmental Engineering.

Address: Corso Duca Degli Abruzzi, 24, Turin, 10129, Italy

Phone: +393335343070

E-mail: Jonathan.melchiorre@polito.it

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