Performance assessment and improvement of automated structural seismic design of RC systems per EC08 and RPA2024

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RESUME The Architecture-Engineering-Construction industry is witnessing a strong push toward automating the entire construction process. Building Information Modelling (BIM) has been pivotal in facilitating this automation across various stages of construction. However, challenges persist, particularly in interfacing between disciplines during the early design phases. Recently, advancements in Artificial Intelligence have enabled the development of innovative methods for automating and optimizing the structural design. In this context, the present paper proposes an algorithm tailored for reinforced concrete structural systems as defined by EC08 and RPA2024 standards. The study evaluates the robustness and performance of automated structural design for RC systems across diverse architectural configurations. Additionally, the research emphasizes fine-tuning algorithm parameters to enhance the performance of optimized layouts, which are evaluated using response spectrum analysis. The ultimate objective is to develop seamlessly optimized and code-compliant structural solutions.

Mots-clefs Structural design automation, Structural design optimization, Seismic design, Architecture-Engineering interface.

I. INTRODUCTION

The Architecture-Engineering-Construction (AEC) industry is undergoing a profound transformation driven by a need for increased efficiency, accuracy, and sustainability in the construction process. A central enabler of this transformation is Building Information Modelling (BIM), which has emerged as a pivotal technology for integrating design, analysis, and construction workflows (Khan et al., 2021; Biswas et al., 2024). Despite these advancements, significant challenges remain, particularly in the early design phases where effective interdisciplinary collaboration is critical (Singh et al., 2022).

Among the challenges faced by the AEC industry, the automation of structural design within the BIM framework has proven particularly complex. Structural engineering requires the harmonization of architectural intent with code-compliant and performance-optimized structural systems in an iterative process. These demands necessitate innovative solutions that go beyond traditional approaches. Recent advancements in Artificial Intelligence (AI) and machine learning have demonstrated considerable promise in automating complex tasks in structural design, ranging from topology optimization to performance evaluation (Qin et al., 2024; Zhao et al., 2023; Bourahla et al., 2024). Further studies have focused on automating and optimizing RC and cold formed steel design within BIM environments to improve interdisciplinary collaboration at an early stage of the design (Bourahla et al., 2023; Bourahla et al., 2022; Tafraout et al., 2019). In this context, the present study builds upon these recent advancements by introducing a new criterion in the objective function to enable the selection of the lateral load resisting system as per EC08 (CEN, 2004) and RPA2024 (CGS, 2024). The proposed methodology is validated through performance assessment of structural layouts generated from different architectural configurations using push-over analysis, demonstrating its robustness and potential to streamline the structural design process in the AEC industry.

II. CONCEPT OF THE INTELLIGENT AUTOMATIC STRUCTURAL DESIGN

The protocol for intelligent automatic structural design presented in this paper begins by identifying potential positions for the structural elements of a building's skeleton, derived from an architectural configuration provided in IFC format from a BIM platform. At this stage, only basic architectural features—such as interior partitions, exterior walls, openings (windows and doors), and floor outlines—are required. Subsequently, a hill climbing algorithm (HCA) is applied to generate an optimal arrangement of column axes along two perpendicular directions, forming the building's skeleton. In the final step, a genetic algorithm is employed to optimize the distribution of shear walls (SWs) within the predefined skeleton. Details regarding the constraints and the multi-objective parameters involved in this process are discussed in Bourahla et al. (2023) and elaborated further in the subsequent sections, where the modified criteria in the objective function are detailed. This early-stage framework benefits both architects and engineers by offering insights into structural alternatives, minimizing extensive design iterations, and facilitating a more efficient convergence toward the final design.

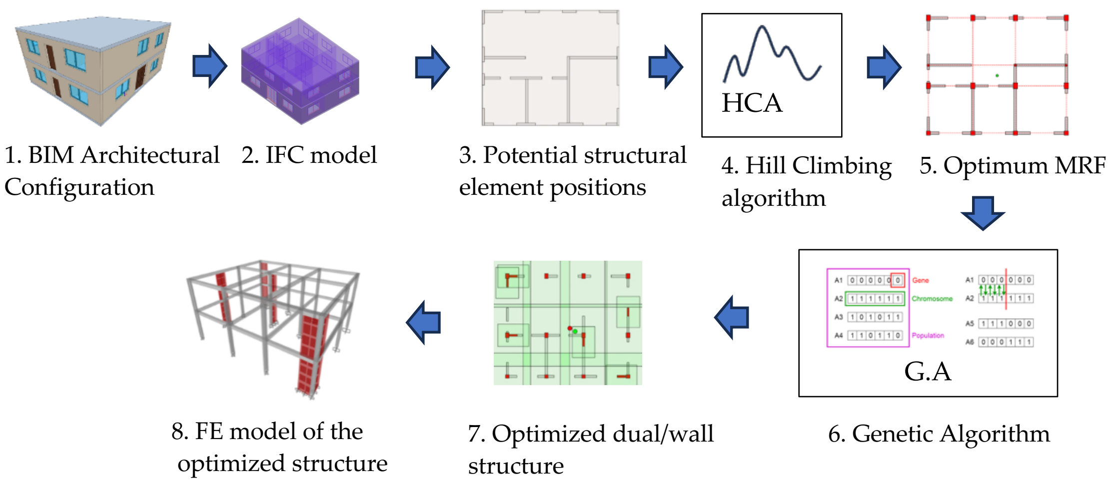


FIGURE 1. The concept of intelligent automatic structural design

III. RC structural systems as per EC08/RPA2024

The European seismic code EC8 and the Algerian seismic code RPA2024 have a similar approach when classifying reinforced concrete structural systems' behavior under horizontal seismic actions.

The presented study focuses on four of those systems, frame systems, dual systems equivalent to frame systems, dual systems equivalent to wall systems and wall systems. The classification is based on the ratio of the shear resistance provided by the frames (or walls) to the total shear resistance of the entire structural system. The structural systems and their corresponding shear resistance ratio limits are defined in **TABLE 1**.

TABLE 1. RC structural systems classification

Structural systems	Ratios of shear resistance of frames (K)
Frame system	$K > 65$ %
Dual system equivalent to frame	50 % < $K \leq$65%
Dual system equivalent to wall system	35 % < $K \leq$50%
Wall system	$K \leq 35$ %

For the purpose of this study, the ratio of the columns' shear resistance at the building base compared to the total shear resistance *K*, is estimated for a given direction, using Eq. (1).

$$K = \frac{\sum I_c}{\sum I_c + \sum I_w} \tag{1}$$

Where I_c is the inertia of the column, and I_w is the inertia of the shear walls along one direction.

IV. Constraints and Objective function

The goal of the optimization is to develop a structural system that adheres to a set of rules and constraints derived from experience and replicates the engineer's conceptual reasoning. The application of these rules is evaluated using an objective function. The objective function described in Bourahla et al. (2023) is employed in this work, with an additional feature enabling the selection of the desired structural system from those outlined in Section III. The constraints have been adjusted to eliminate potential conflicts with the requirements of the selected structural system, such as the length and gravity load overlapping area of the shear walls.

Furthermore, a new score, S_{score}, is introduced to the objective function to ensure that the final solution complies with the user-defined desired structural system. If no preference is specified for selecting a specific structural system among those listed in Table 1, a weight value of 0 can be assigned to the S_{score} criterion.

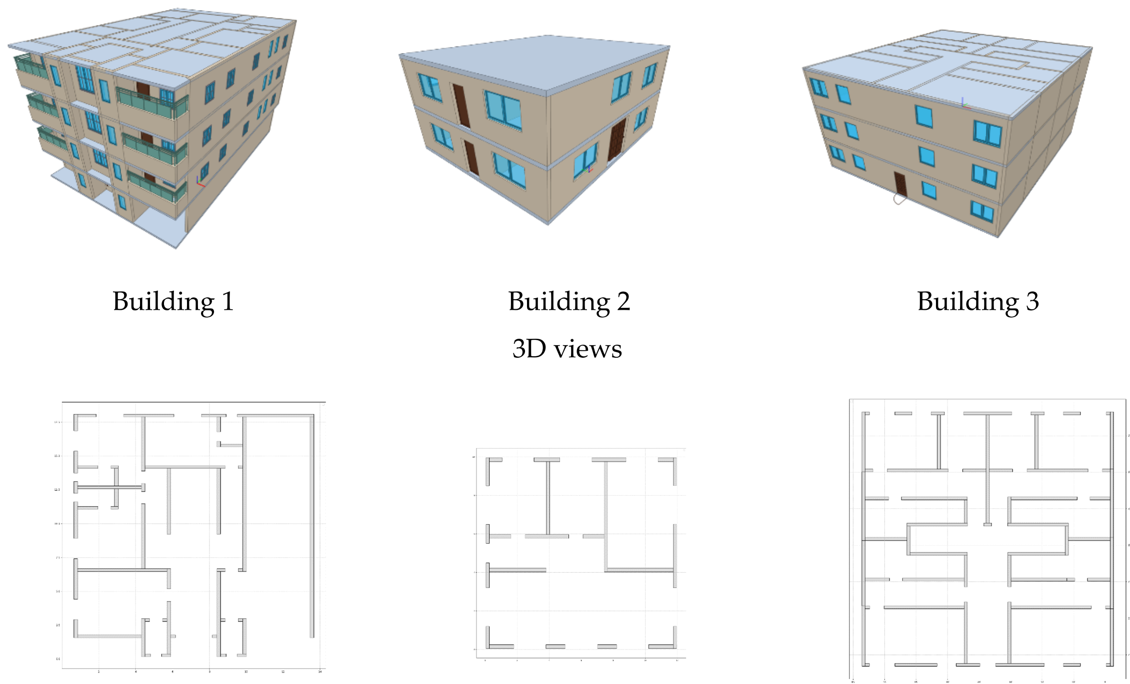
Eq. (2) calculates the compliance of the solution with the desired structural system, where each system is defined by possible values intervals $[a, b]$ (**TABLE 1**) and a reference ratio K_{ref}. The score decreases linearly from 1, representing complete compliance, to 0 when *K* reaches the limit of the possible values. Alternatively, non-compliance is penalized with a score of -1.0.

$$S_{score}(system) = \begin{cases} 1 - \dfrac{\left|K - K_{ref}\right|}{b - a}, & K \in [a, b] \\ -1 \quad , & K \notin [a, b] \end{cases} \tag{2}$$

The reference ratio K_{ref} for frame systems is 1, which indicates that the structure is entirely composed of frames. For wall systems, K_{ref} is 0 which signifies a structure that relies entirely on walls. For both types of dual systems, initial experiments with the algorithm showed that the center of the interval $[a, b]$ represents the ideal value for K_{ref}. This facilitates the algorithm's convergence to values within the interval while avoiding its boundaries.

V. CASE STUDIES: ROBUSTNESS AND PERFORMANCE EVALUATION

To assess the robustness of the proposed method, three distinct architectural configurations are evaluated (Fig. 2). For each building, the algorithm is tested with all four structural systems imposed consecutively as an objective criterion, as expressed in Eq. (2) to evaluate its effectiveness in converging to the desired target system.



Plan views

FIGURE 2. Three architectural configurations

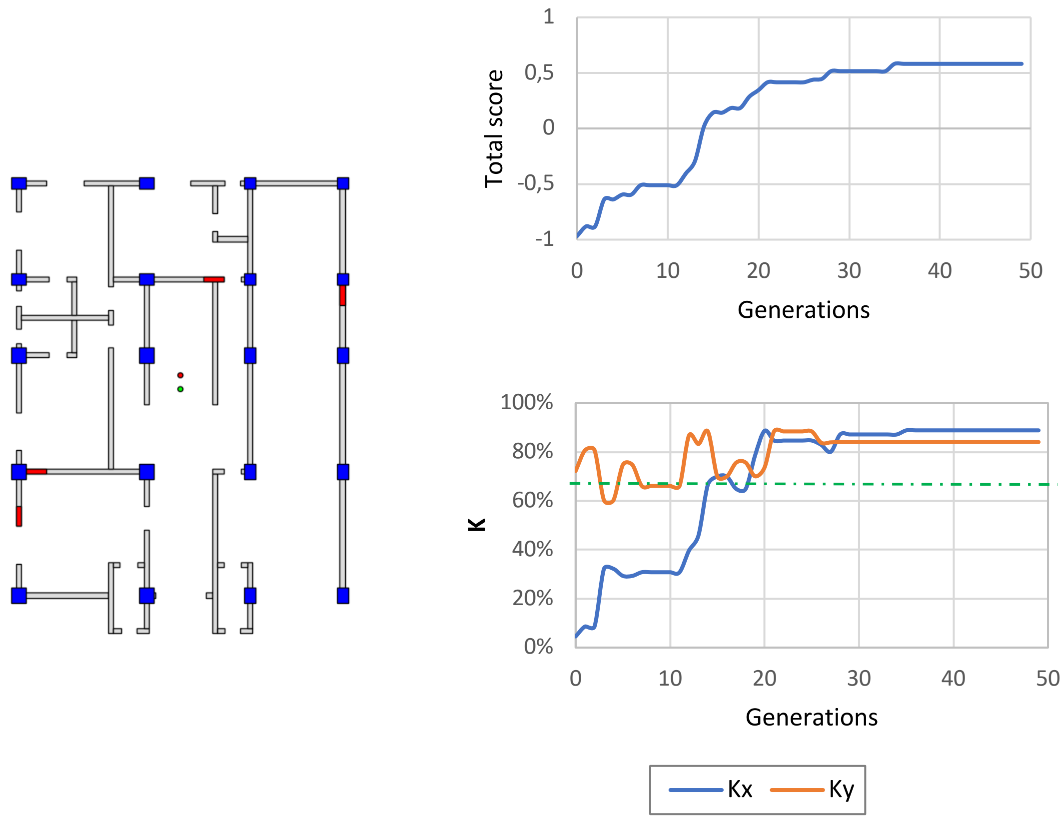
Initially, the algorithm is tested on Building 1 to observe the evolution of the new score in both directions and its impact on the total score. Fig. 3 summarizes the optimization results for each target system. Alongside the final solution, the graphs illustrate the progression of the total score and the K ratio in both directions over the iterations.

In the case of a frame system, the K_X ratio initially started at a low value, leading to a penalty in $S_{system\ X}$. However, after three iterations, the ratio began to recover, eventually reaching 88%. In the Y direction, the ratio started at approximately 77% and fluctuated before stabilizing at 84%. This convergence influenced the total score, with the algorithm achieving its best performance as soon as the K ratios stabilized.

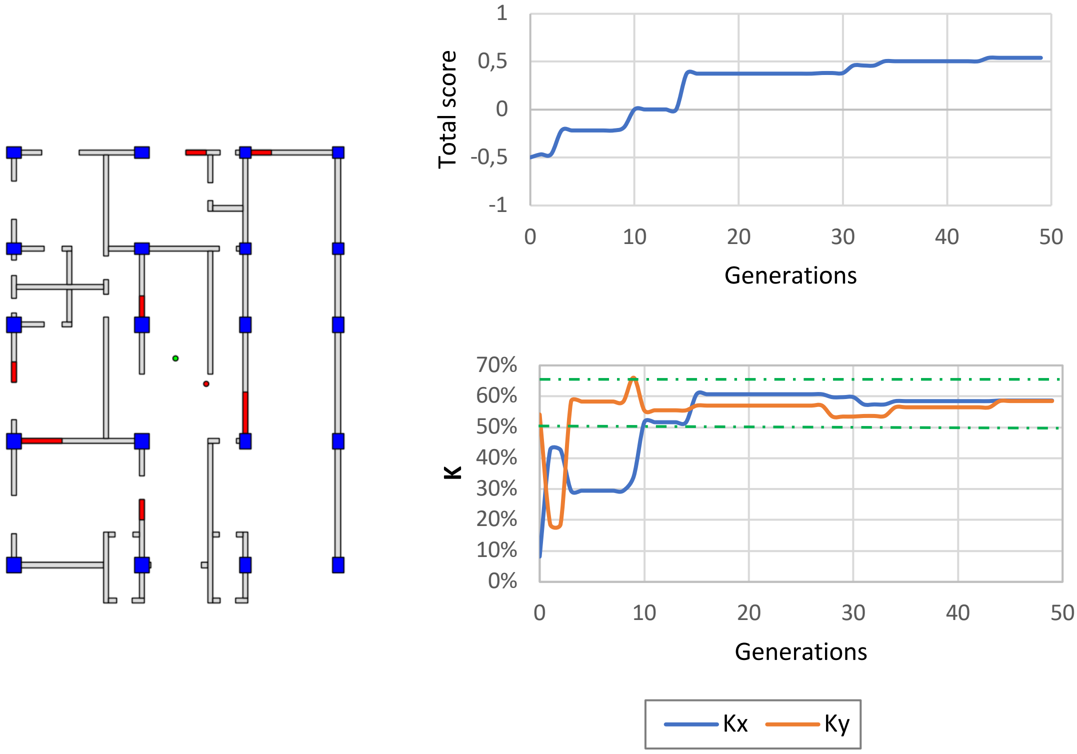
For the case of a dual system equivalent to frame, the algorithm converged to an acceptable ratio relatively quickly in the X direction, and demonstrated a rapid recovery in the Y direction after the objective function was penalized.

For the dual system equivalent to a wall system, a similar behavior to the dual system equivalent to frame was observed. The algorithm required only five iterations to enter the range of accepted values and find an optimal solution in both directions.

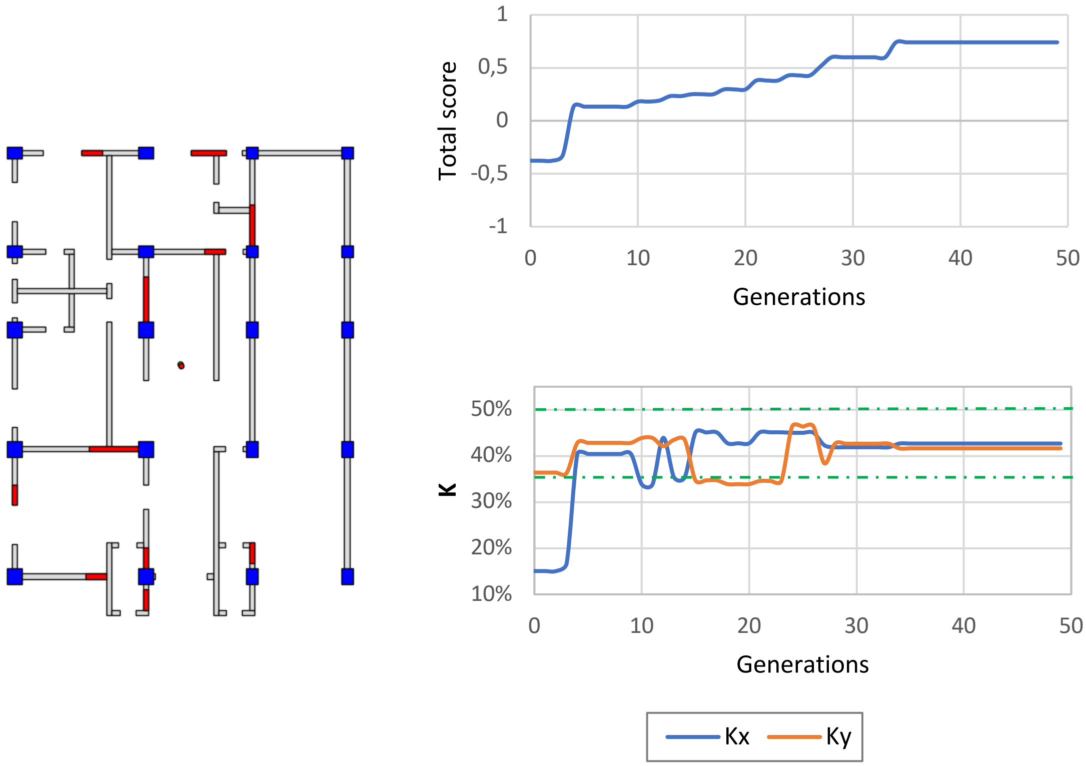
Finally, for wall systems, the algorithm exhibited smooth convergence to the desired configuration. In this case, changes in S_{system} had minimal impact on the total score, indicating that other constraints, such as floor torsional eccentricity and radius constraints, had a greater influence on the optimization process.



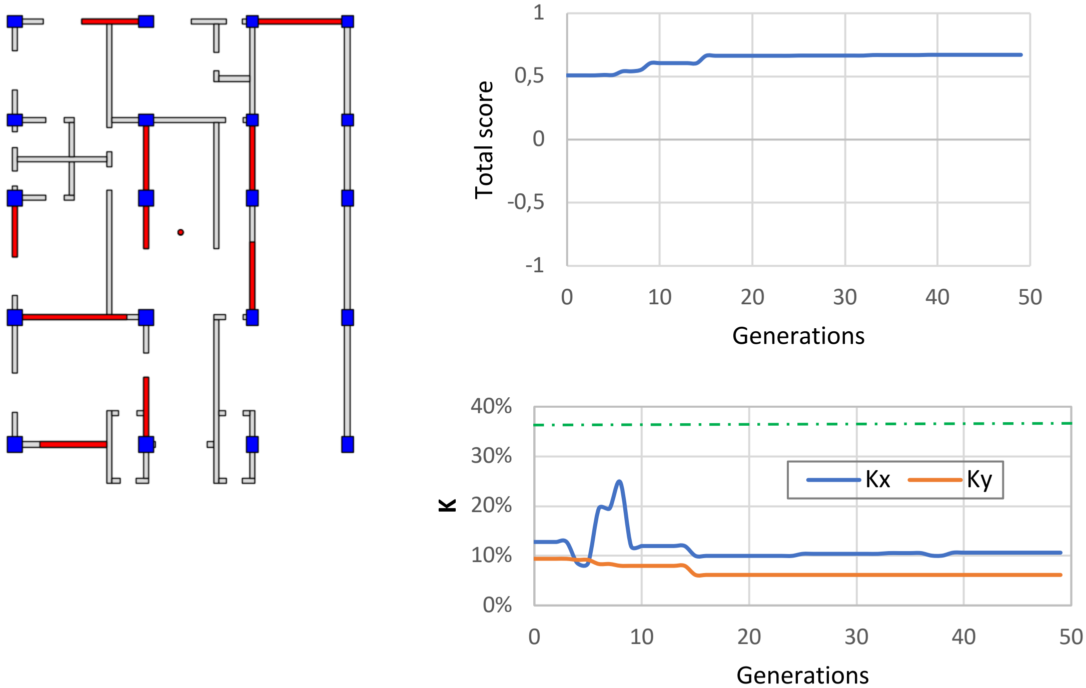
(a) Frame system



(b) Dual system equivalent to frame system



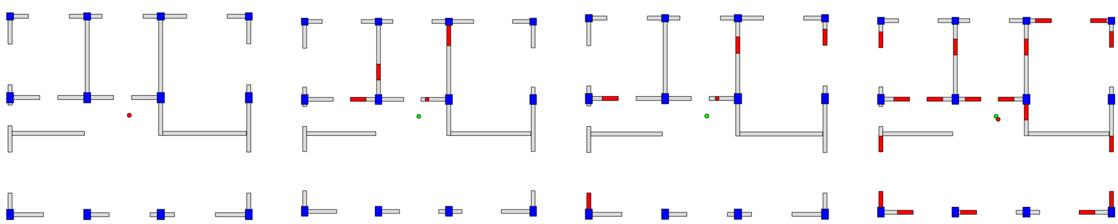
(c) Dual system equivalent to wall system



(d) Wall system

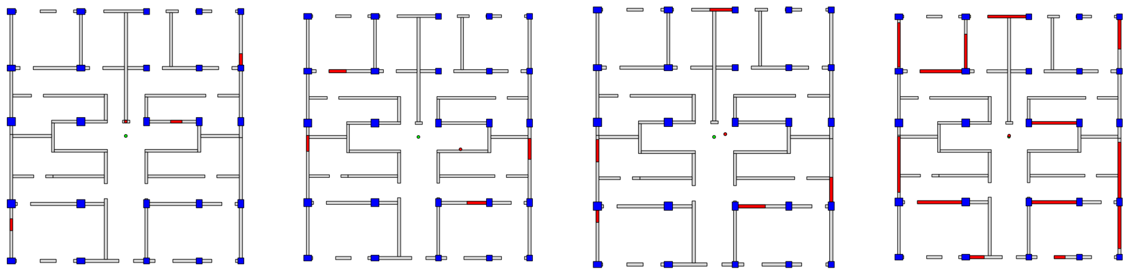
FIGURE 3. Generated layouts of structural systems, K ratios and total scores

Figs. 4 and**Erreur ! Source du renvoi introuvable.** summarize the results of the optimization for the building 2 and 3. In gray are the architectural partitions, in blue, the columns, and in red the positions of shear walls as recommended by the algorithm. In addition, the green and the red circles represent the center of mass and of stiffness of the floor respectively. The results show that in addition to converging to a system close to the desired system, the algorithm converged to solutions with appropriate floor torsional eccentricity and radius. In general, the generated layouts, as illustrated in Fig. 3, 4 and 5, show that the HCA algorithm performed exceptionally well in selecting the column positions and defining the frame axes. Additionally, the GA algorithm successfully converged to the target systems across all configurations. However, the wall positions and distributions indicate a need for incorporating additional constructability provisions as constraints and further refinement of the objective function criteria.



Frame system Dual frame system Dual wall system Wall system

FIGURE 4. Generated structural layouts for building 2

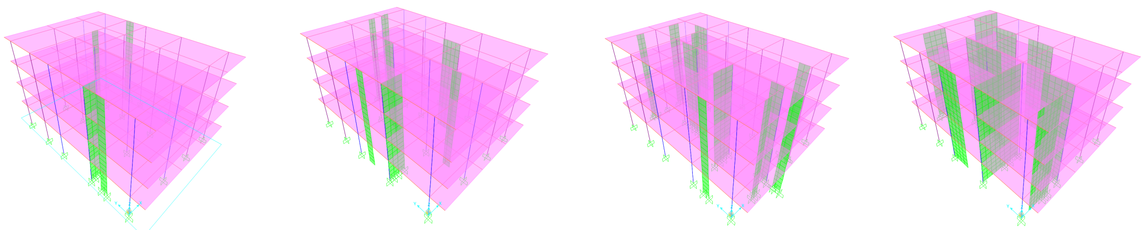


Frame system | Dual frame system | Dual wall system | Wall system

FIGURE 5. Generated structural layouts for building 3

VI. STRUCTURAL ANALYSIS OF THE GENERATED STRUCTURES

To evaluate the structural performance of the buildings generated by the genetic algorithm (GA), 3D numerical models of four configurations of Building 1 were developed using BIM-compatible finite element software SAP2000 (Fig. 6). The assessment aimed to demonstrate that the design constraints specified as requirements were met.



Model 1 Frame system | Model 2 Equivalent frame system | Model 3 Equivalent wall system | Model 4 Wall system

FIGURE 5. 3D-FE models

Table 2 compares the base shear resistance ratio *K* obtained using the simplified Eq. (1)—which serves as an objective function criterion in the GA—with the corresponding results from the 3D FE models. The table demonstrates that the *K* ratios satisfy the desired classification conditions and shear force ratios obtained from the FE models are, in most cases, consistent and coherent.

Table 2. Comparison of the shear ratio (K) between the FE-models and the simplified Eq.1

Model		Direction	Base shear ratio		
			K (FE)	**K (GA)**	**Classification range**
1	Frame system	X	73%	89%	K > 65%
		Y	78%	90%	
2	Equiv. Frame system	X	50%	62%	50 % < K ≤ 65%
		Y	46%	60%	
3	Equiv. Wall system	X	44%	44%	35 % < K ≤ 50%
		Y	31%	44%	
4	Wall system	X	13%	6%	K ≤ 35 %
		Y	9%	11%	

The torsional rigidity criterion is also met as none of the fundamental modes exhibit torsional behavior. Moreover, all structures produced by the genetic algorithm (GA) meet the drift story criterion (Table 3).

Table 3. Story drifts

Model		Max. story drift (%) X	Max. story drift (%) Y	Model		Max. story drift (%) X	Max. story drift (%) Y
1	**Frame syst.**	35	25	3	**Equiv. wall syst.**	16	11
2	**Equiv. frame syst.**	28	21	4	**Wall syst.**	4	4

The calculated percentages of maximum steel reinforcement for columns and beams, as determined by the finite element (FE) models per the Eurocode (EC), fall within the required minimum and maximum ranges specified by RPA2024. However, the required reinforcement for the walls in both the frame and equivalent frame systems exceeds the typical percentages outlined in Table 4.

Table 4. Maximum steel reinforcement ratios

Model		Column ratios (%)			Beam ratios (%)			Wall ratios (%)		
		Min.	**EC**	**Max.**	**Min.**	**EC**	**Max.**	**Min.**	**EC**	**Usual**
1	**Frame syst.**	*1.0*	2.9	*4.0*	*0.5*	2.4	*4.0*	*0.25*	4.9	*2.0*
2	**Equiv. Frame syst.**	*1.0*	2.7	*4.0*	*0.5*	1.2	*4.0*	*0.25*	4.9	*2.0*
3	**Equiv. Wall syst.**	*1.0*	1.7	*4.0*	*0.5*	1.8	*4.0*	*0.25*	2.5	*2.0*
4	**Wall syst.**	*1.0*	1.0	*4.0*	*0.5*	2.2	*4.0*	*0.25*	1.1	*2.0*

VII. CONCLUSION

The automation of structural design in the AEC industry offers significant potential to industrialize processes and enhance design efficiency. In this study, an automation framework was assessed and demonstrated robust performance across three distinct architectural configurations, effectively converging to the desired structural systems as classified by EC08 and RPA2024 with high accuracy. The algorithm consistently optimized the total score by achieving target stiffness ratios in both directions within a minimal number of iterations. Notably, the convergence behavior varied across systems. The results for all buildings reinforced the algorithm's effectiveness in generating optimal layouts, ensuring appropriate floor torsional eccentricity and radius, while successfully placing columns and shear walls. However, the positioning and distribution of walls highlighted the need to incorporate additional constraints, such as constructability provisions, to enhance practicality. To validate these results based on simplified criteria, the generated structures were analyzed using response spectrum analysis. Both the base shear force classification ratios and the primary seismic design requirements were found to be satisfactory for most structures. However, in dual systems, the reinforcement ratios of shear walls tend to be relatively high due to the limited number of shear walls in the generated layouts.

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