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Structural optimization of reinforced concrete frames with a modified flower pollination algorithm

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Abstract

Reinforced concrete (RC) frames represent the most common structural system in the built environment. Therefore, their efficient design is expected to offer significant economic and environmental benefits. Simultaneously, the optimal design of RC frames remains a complex computational task requiring efficient numerical algorithms. Herein, a variant of the established Flower Pollination Algorithm (FPA) is applied to the optimal design of RC frames. The new variant, called Flower Pollination Algorithm with Pollinator Attraction (FPAPA), accounts additionally for the evolutionary mechanism of *pollinator attraction* in the natural process of flower pollination. FPAPA is applied to benchmark problems in the structural optimization of concrete frames with known global optimum solutions. It is found that FPAPA offers high quality design solutions within limited computational budgets. Furthermore, comparisons show that FPAPA represents a competitive or superior alternative to the most well-known optimization algorithms.

Keywords: Reinforced concrete; Structural optimization; Flower Pollination Algorithm; Pollinator attraction

1 Introduction

Reinforced concrete (RC) is the most common structural material in built environment. However, its construction is associated with high economic costs and environmental footprint [1-5]. Hence, designing efficiently RC structures is expected to play a key role in sustainable construction [1-5]. Concrete structures employ a wide range of structural systems. Amongst them, RC frames represent the most frequent one as they combine economy, aesthetics, versatility in configuration and reliability in structural response. Simultaneously, the efficient design of concrete frames remains a challenging task due to the numerous design variables and the complex interactions when calculating both the design objectives and constraints [6]. Therefore, the use of numerical algorithms is promising in material efficient design of concrete frames. Gradient-based optimization algorithms are known to converge faster to optimum

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solutions. Nevertheless, their application necessitates calculation of gradients that are not readily available in RC frames design [7]. As a result, the use of evolutionary algorithms is gaining more ground in the automation of RC frames design, such as the Genetic Algorithm (GA) [8], Simulated Annealing [9], Particle Swarm Optimization (PSO) [10], Flower Pollination Algorithm [11] and many others. Despite the advantages of evolutionary algorithms when optimizing RC frames, they still lack certainty in tracking global optimum solutions and often demonstrate slow rates of convergence. The latter drawback combined with the high computational costs for complex RC frames turns the optimal design of real-world RC frames not applicable in standard engineering practice. It is therefore essential that efficient evolutionary algorithms are developed to tackle the structural optimization of RC frames.

Numerous research efforts examine the application of evolutionary algorithms to the optimum design of 2D concrete frames (e.g. [12-17]). However, the number of studies optimizing 3D RC frames is still rather limited [18-28]. The latter observation could be attributed to the additional computational cost and complexity of numerical procedures associated to the 3D concrete frames structural design. The first author of this study examined structural optimization of 3D RC frames by using the FPA [27]. It was observed that FPA provides similar quality results to other well-known algorithms when applied to small-scale RC frames, but with slightly slower convergence rates. Furthermore, it outperforms other optimization algorithms when applied to large and complex RC frames due to its high capacity of exploring the search space.

The FPA was originally developed by the second author of this chapter [11] as a metaheuristic, algorithm that imitates evolution of flowers. The main advantages of FPA are its high computational efficiency, mostly in terms of exploration potential, and the formulation simplicity. Consequently, FPA has been extensively used in literature to optimize numerous and diverse optimization problems in different scientific fields (e.g. [29-38]). Furthermore, a significant number of hybridized and modified FPA versions have been developed to enhance its performance for various optimization tasks. For example, Yang et al. [39] developed a multi-objective version of FPA. Abdel-Raouf *et al.* [40] enhanced computational performance of FPA by employing chaotic maps. In their study, Rodrigues et al. [41] formulated a binary variant of FPA to tackle combinatorial optimization tasks. Wang et al. [42] combined FPA with a bee-pollinator to conduct cluster analysis. Tamilselvan and Javabarathi [43] formulated a multi-objective FPA variant to solve the capacitor placement problem. Abdel-Basset and Hezam [44] developed a hybrid FPA variant using a local-search algorithm. Hezam et al. [45] formulated another hybrid FPA with tabu search. Nigdeli et al. [46] used a hybrid FPA with harmony search for optimizing the tuning of mass dampers in structural systems. Zhou et al.

[47] formulated a discrete greedy FPA that was applied to the spherical traveling salesman problem. Abdel-Basset et al. [48] used crossover to modify FPA and apply it to the knapsack challenge. In [49], the strategy of island population is employed for mitigating early FPA convergence. In [50], a new FPA version is constructed by generating global orientations of all flowers in the population. Ozsoydan and Baykasoglu [51] enhanced FPA by chaos and intensification. Moreover, Ozsoydan and Baykasoglu [52] developed a species based FPA with enhanced intensification.

In [53], Mergos and Yang developed an FPA variant considering an extra feature of flower pollination called *pollinator attraction* [54-55]. The latter feature addresses the observation that flowers are evolving to attract pollinators and spread their pollen in the population. Consistently, FPAPA offers fitter flowers an enhanced probability to manage transfer of pollen through biotic pollination. FPAPA was tested against the benchmark suite of single-objective, real-parameter optimization problems specified in IEEE-CEC'13 [56], and it was found to offer a statistically important improvement in relation to the original version [53].

In the current study, FPAPA is used to the structural optimization of small-scale benchmark RC frames and its computational performance is evaluated against competitor algorithms. All RC frames are duly designed according to the specifications of the Eurocodes [57-59]. Furthermore, the global optimal solutions of the RC frames are pre-known from exhaustive search. Hence, the efficiency of the algorithms is measured in actual errors against the global optima.

In the following sections, the optimal structural design problem of concrete frames is first explained. Then, the algorithmic formulation of FPAPA is described. Next, a set of benchmark RC frames is introduced with their known global optimal solutions. Finally, FPAPA is applied to optimize the benchmark RC frames and its performance is ranked against other algorithms. Useful conclusions and future recommendations are made.

2 Optimization problem

The main objective of the present optimization problem is to reduce the materials cost of real-world RC frames in a way that satisfies the structural design requirements set by current guidelines like the Eurocodes [57-59]. More specifically, the optimization problem herein searches for the optimal combination of RC members' cross-sections that leads to minimum material economic cost. In this effort, external loads, frame geometry, boundary conditions and material properties are taken as pre-determined. Hence, the design variables vector $\mathbf{x}$

consists of cross-sections attributed to different structural members groups in the concrete frames. Moreover, following real-world applications, cross-sections are taken from discrete, pre-known lists. The afore-described optimization task is expressed as:

$$\begin{aligned}
&\text{Minimize:} && F(\mathbf{x}) \\
&\text{Subject to:} && g_j(\mathbf{x}) \leq 0, \quad j = 1 \text{ to } m \\
&\text{Where:} && \mathbf{x} = (x_1, x_2, \dots, x_d) \\
&&& x_i \in \mathbf{D}_i = (1, 2, \dots, k_i), \quad i = 1 \text{ to } d
\end{aligned} \tag{1}$$

In this equation, $F(\mathbf{x})$ represents the objective function aiming to minimize, and $\mathbf{x}$ stands for design variables vector that includes d number of variables x_i ($i = 1$ to d), indicating member cross-sections. Hence, d coincides with the number of groups with possibly different cross-sections. These variables x_i assume values from sets of integer values $\mathbf{D}_i = (1, 2, \dots, k_i)$ indicating the locations of cross-sections in their allocated lists and k_i stands for the length of the corresponding list attributed to group i . Moreover, the solution should satisfy m design constraints $g_j(\mathbf{x}) \leq 0$ ($j = 1$ to m).

The objective function $F(\mathbf{x})$ is calculated from Eq. (2), where V_c (m^3) denotes concrete volume and m_s (kg) denotes the mass of rebars including both the longitudinal and transverse reinforcement. In Eq. (2), f_{co} and f_{so} are material costs of concrete per m^3 and rebars per kg, respectively. The material unit prices adopted in this study are: $f_{co} = 100\text{€/m}^3$ and $f_{so} = 1\text{€/kg}$.

$$F(\mathbf{x}) = V_c(\mathbf{x}) \cdot f_{co} + m_s(\mathbf{x}) \cdot f_{so} \tag{2}$$

In Eq. (2), the calculation of $V_c(\mathbf{x})$ is straight-forward from the design vector $\mathbf{x}$ (i.e. member cross-sections) and frame geometry. However, for the same $\mathbf{x}$ vector, the steel reinforcement mass $m_s(\mathbf{x})$ is calculated by structural analysis and design procedures. The latter procedures are nonlinear and complex working essentially like black-box functions in optimization problem.

More particularly, herein, the design rules and specifications of Eurocodes [57-59] are employed to determine $m_s(\mathbf{x})$. To facilitate this task, structural analysis and design is performed with the computer software SAP2000 [60]. A detailed description of the structural analysis and design procedures followed in SAP2000 for concrete frames can be found in [27, 61]. It is also noted that an in-house application in MATLAB [62], called STROLAB (i.e. STRuctural Optimization LABoratory) [27] has been developed to interact with SAP2000 for the purposes of this optimization framework.

Following the afore-described procedures, concrete columns and beams are first designed for axial loads, bending, torsion and shear at different locations along their lengths. The outcomes of structural design are the areas of required longitudinal and transverse reinforcement at the respective member cross-sections. These areas are multiplied by their application lengths and then are summed to calculate $V_c(\mathbf{x})$ and finally $m_s(\mathbf{x})$. In this procedure, it is taken for simplicity that the provided rebar areas at the design cross-sections match exactly the required ones and that these areas are applied up to the neighbouring member sections with smaller steel reinforcement requirements.

The constraints $g_j(\mathbf{x}) \leq 0$ ($j = 1$ to m) stand for the design checks prescribed by the Eurocodes [57-59] at the Ultimate and Serviceability and Limit States (ULS and SLS). For the ULS, design checks for local flexural and shear resistance, a constraint is considered violated when the respective checks are not satisfied by any permitted area of rebars inside the cross-sections. The afore-described approach is followed since only the member cross-sections act as design variables. Hence, if ρ_w and ρ_l are the required transverse and longitudinal reinforcing steel volumetric ratios and $\rho_{w,max}$ and $\rho_{l,max}$ their respective maximum limits according to Eurocodes and construction practice, then the following inequalities should apply:

$$\rho_w - \rho_{w,max} \leq 0 \quad (4)$$

$$\rho_l - \rho_{l,max} \leq 0 \quad (3)$$

Moreover, the design constraints at the ULS against diagonal compression failure are considered not to be met when the combination of torsion and shear demands exceeds the maximum strength of diagonal compressive struts in concrete members. The latter constraints are expressed as below, where V_{Ed} and T_{Ed} represent acting shear forces and torsional moments, respectively, and $V_{Rd,max}$ and $T_{Rd,max}$ denote the respective resistances of the diagonal compression struts for an angle $\theta = 45^\circ$.

$$\frac{V_{Ed}}{V_{Rd,max}} + \frac{T_{Ed}}{T_{Rd,max}} - 1 \leq 0 \quad (5)$$

For the Serviceability Limit State (SLS), designs checks ensure that displacements and deformations do not exceed permissible values. The corresponding design constraints are

written as follows, where Δ represents the displacement/deformation demand for the SLS load combination and Δ_{max} the respective permissible value.

$$\Delta - \Delta_{max} \leq 0 \quad (6)$$

From the previous, it is inferred that design constraints work also as black-box functions since they are calculated from complex structural design and analysis procedures in the RC frames. This enhances further the complexity of the optimization task. Finally, it is noted that, in the current study, the penalty function approach is adopted to account for the violation of design constraints.

3 FPAPA algorithm

FPA is imitating how flowers are reproduced in nature. This process is so successful that flowers have dominated the landscape of planet earth [63]. Similar to all biological organisations, flowers aim at reproduction. The latter is achieved through pollination. Pollination is either biotic or abiotic [11]. In the former case, the transfer of pollen is achieved via pollinators (i.e. insects and animals). Pollinators can make long flights. Therefore, biotic pollination works like global search [11]. Moreover, pollinator flights resemble Lévy flights [64]. Abiotic pollination entails pollen transfer via the wind or water. The reproduction of grass is a typical example of abiotic pollination [11, 63]. Abiotic pollination, typically, happens locally. Hence, it can be modelled as local search [11]. Another flower pollination feature is the so-called constancy. With constancy, pollinators prefer specific species bypassing others reducing the risks coming from exploring unknown flower species [11].

The previous observations have been idealized in the following basic rules of the original FPA:

1. Biotic pollination is assumed as a global search mechanism where pollinators perform Lévy flights.
2. Abiotic pollination is treated as a local search procedure.
3. The reproduction probability is proportional to the similarity of flowers involved due to flower constancy.

4. The pollination procedure (global vs local) is selected by a probability switch value p that belongs in $[0, 1]$.

According to the 1st and 3rd FPA rules, the biotic pollination mechanism can be idealized as follows:

$$\mathbf{x}_i^{t+1} = \mathbf{x}_i^t + \gamma \cdot L(\lambda) \cdot (\mathbf{g}^* - \mathbf{x}_i^t), \quad (7)$$

where $\mathbf{x}_i^t$ reflects flower i in the population at iteration t and $\mathbf{g}^*$ stands for the fittest flower in the population, λ is a positive constant that is suggested to be taken as 3/2 [11], γ represents a step size scaling factor, and $L(\lambda) > 0$ stands for the size of the flight step. More specifically, $L(\lambda)$ follows a Lévy distribution shown below:

$$L \sim \frac{\lambda \Gamma(\lambda) \sin\left(\frac{\pi\lambda}{2}\right)}{\pi} \cdot \frac{1}{s^{1+\lambda}}, \quad (s > 0), \quad (8)$$

where $\Gamma(\lambda)$ represents gamma function with $s > 0$. On the other hand, the 2nd and 3rd rule are idealized by Eq. (9), where $\mathbf{x}_j^t$ and $\mathbf{x}_k^t$ represent other flowers in the same population and ε is a random number withdrawn in $[0, 1]$ assuming uniform distribution. Finally, following the 4th rule of the original FPA, the type of flower pollination is determined by comparing a random number in $[0, 1]$ against p . If the random number is smaller than p , the global pollination mechanism is invoked.

$$\mathbf{x}_i^{t+1} = \mathbf{x}_i^t + \varepsilon \cdot (\mathbf{x}_j^t - \mathbf{x}_k^t). \quad (9)$$

Clearly, parameters p and γ should be selected so that they maximize the computational performance of FPA. The authors have conducted a parameters tuning study revealing the optimal FPA parameters values for different optimization problems [65]. In that study, it is suggested that γ ranges between 0.1 and 1 and p ranges between 0.2 and 0.6.

Another mechanism of flower pollination, observed in nature and not considered in the original FPA, is that flower species try to evolve so that they attract pollinators and transfer pollen through biotic pollination [54-55]. This evolution mechanism is observed in many ways. For example, flowers evolve to offer nutritious rewards such as nectar and pollen to entice pollinators (e.g. honeybees). Other flower species develop shapes facilitating access to pollinators (e.g. bowl-shaped flowers) or bright colours attracting pollinators with colour

vision (e.g. birds and bees) or even special scents, such as the case of some flowers species relying on night pollinators (e.g. bats) [54-55]. Perhaps the most characteristic example of pollinator attraction is the case of orchids mimicking female bees in appearance and scent to trick and attract male bees [54-55]. In all cases, pollinator attraction aims at succeeding pollen transfer and reproduction via biotic pollination.

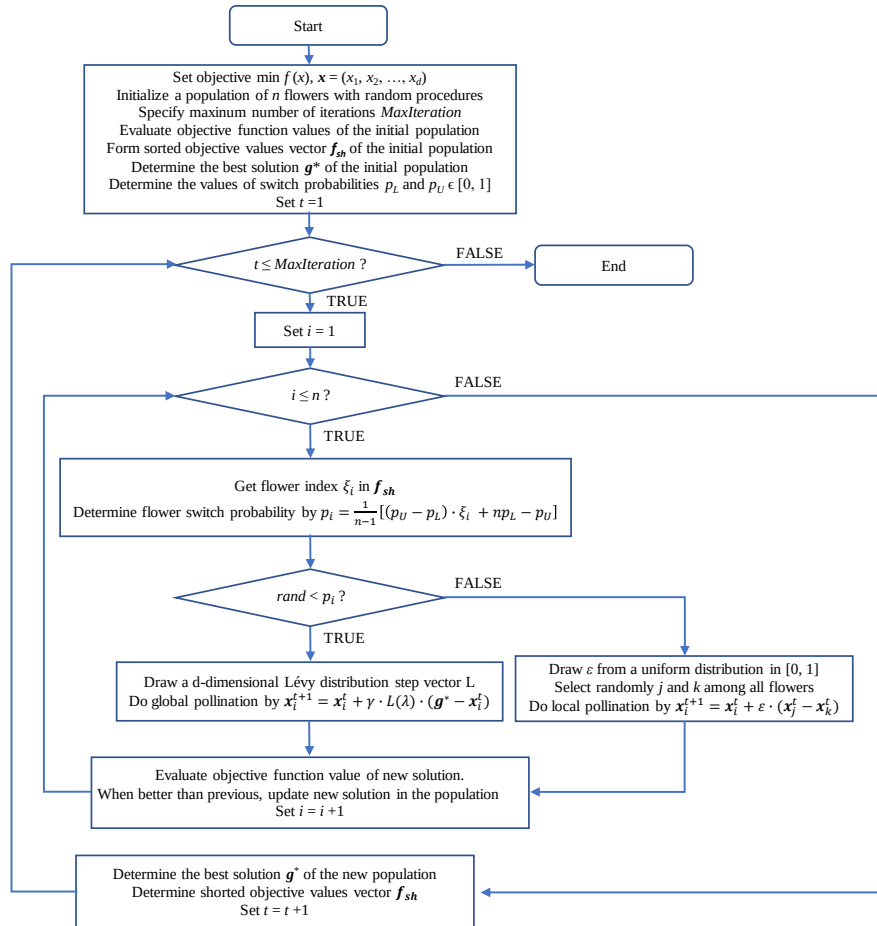


Figure 1: FPAPA flowchart

FPAPA is an FPA variant developed by the authors to account explicitly for the pollinator attraction evolution mechanism [53]. The novel feature of FPAPA is that it increases the chances of fitter flowers to manage pollen transfer through biotic pollination. Consistently, FPAPA assumes that p_i (i.e. switch probability of flower i in the population) varies in accordance with the flower rank within the population. For simplicity, a linear variation of p_i between two limit values p_L and p_U in $[0, 1]$ is assumed, where p_L corresponds to the least fit flower and p_U to the fittest flower. Therefore, if $\mathbf{f}_{sh}$ denotes the sorted (i.e. assuming descending order), vector of objective functions in the previous population and ξ_i represents the position of flower i in $\mathbf{f}_{sh}$, then, in the current population, p_i is given by Eq. (10), where n denotes the size of the flowers population.

$$p_i = \frac{1}{n-1} [(p_U - p_L) \cdot \xi_i + np_L - p_U] \quad (10)$$

It is clarified that in Eq. (10), it should hold $p_U > p_L$ (i.e. maximum probability to conduct biotic pollination for the fittest flower) for consistency with the pollinator attraction rule. Nevertheless, FPAPA works with any p_L and p_U values. As a matter of fact, in the special case where $p_U = p_L$, the proposed variant coincides with the original version of FPA.

Figure 1 illustrates the flowchart of FPAPA. It is observed that the variant follows closely the original FPA apart from the calculation of different switch probabilities for the flowers of the population based on the feature of pollinator attraction. Finally, it is noted that the FPAPA version applied herein rounds the design solutions to their closest integer values to address the discrete nature of the optimization problem under investigation.

4 Benchmark RC frames

Six benchmark RC frames are considered herein originally developed by the first author in [66]. The benchmarks are named by the letter B followed by a number. The geometric configurations of the frames are illustrated in Fig. 2. The benchmark frames have up to three spans and between two and six storeys. Span lengths are equal and either 5 or 6 meters. The heights of storeys are all 3 meters. Concrete grades are from C20/25 to C30/37 as specified in Eurocode 2 (EC2) [57]. Steel reinforcement grade is B500. Cover of concrete to the centroid longitudinal rebars is 50mm. The frames belong to RC buildings that are designed against dead, live and either earthquake or wind loads of different magnitudes. The RC frames are designed to EC2 [57] and EC8 [58] for the Low Ductility Class (DCL) [58]. More details about the structural configuration, material properties, design loads and modelling assumptions of the benchmark RC frames can be found in [66].

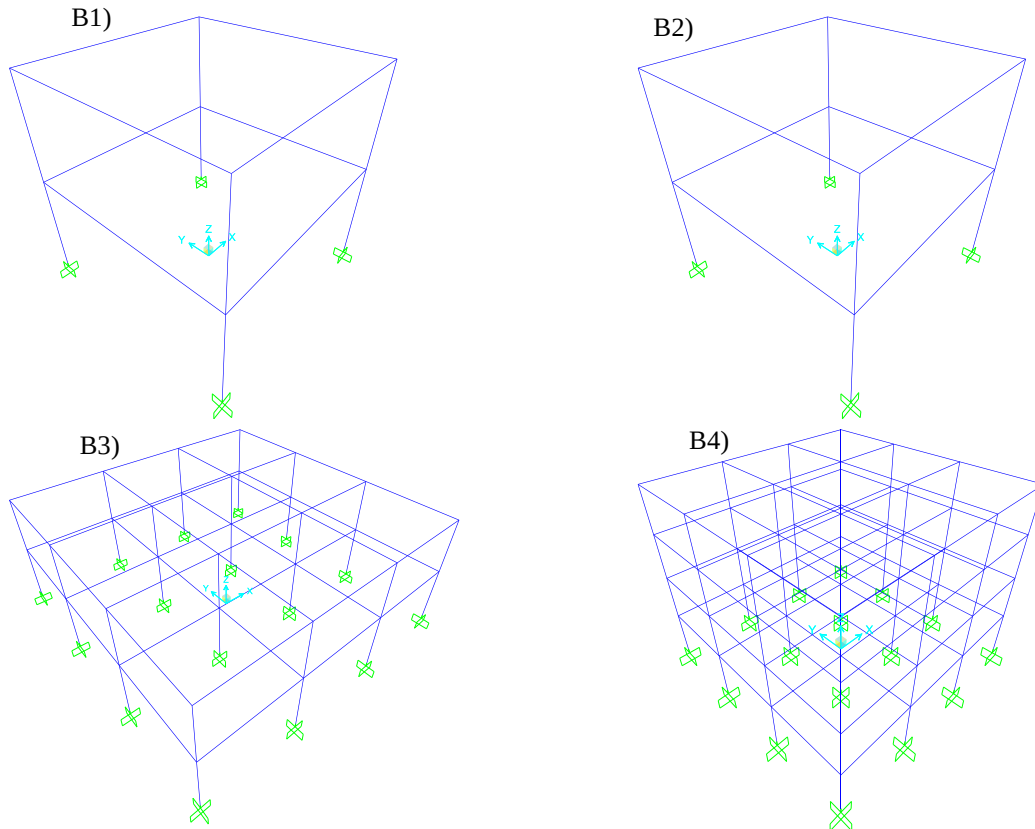
The concrete frames are divided into groups of column and beam members of the same cross-sections. For each group, cross-sections come from pre-determined lists. Therefore, the total number Ω of potential design solutions (i.e. search space) is calculated from the number of member groups and the size of the allocated lists of cross-sections. Finally, the minimum material costs F_{best} are derived from previous exhaustive search analyses. Therefore, it is guaranteed that they represent the global optima of the concrete frames. Table 1 presents the number of design variables, size of search space and minimum material costs of the six RC

frames. More information regarding the arrangement of design variables, member groups and available lists of cross-sections can be found in [66].

As discussed in the previous sections, the objective function $F(\mathbf{x})$ values (i.e. material costs of the RC frames) for each candidate design vector $\mathbf{x}$ should be determined by following a sequence of structural analysis and design procedures for the RC frames that collectively resemble black-box functions. To facilitate optimization studies on the same benchmark problems, the objective function values of all designs are given in a supplementary file of [66] following an exhaustive search analysis by the first author of this chapter.

Table 1: Benchmark RC frames optimization problem properties [66]

Benchmark Frame	d	Ω	F_{best} (Euros)
B1	2	10^2	1350.8
B2	3	10^3	1476.5
B3	4	10^4	10918
B4	6	7^6	13553
B5	5	9^5	4964.3
B6	7	6^7	30060



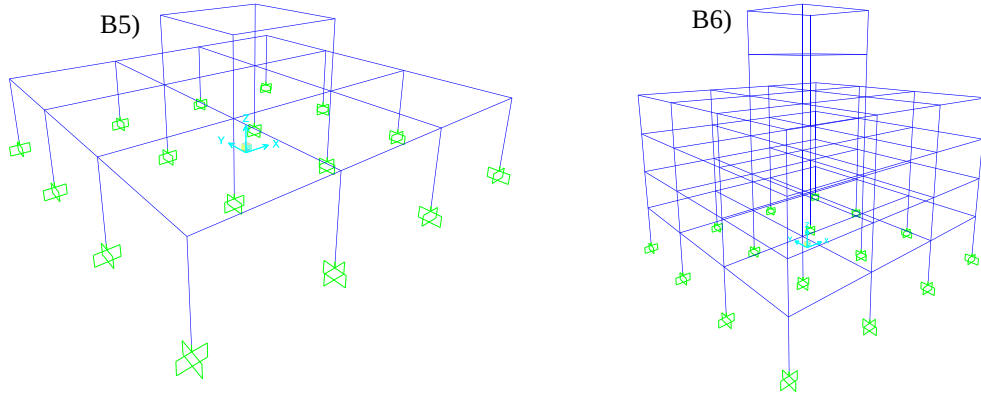


Figure 2: Benchmark RC frames [66]

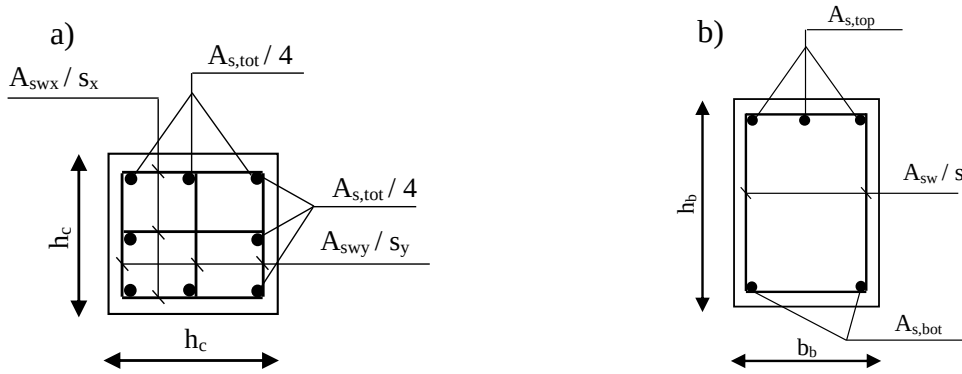


Figure 3: Member cross-sections and configuration of steel reinforcement a) columns; b) beams

5 Performance of FPAPA algorithm

Herein, the performance of FPAPA in optimizing concrete frames discussed above is evaluated. The performance is measured in errors (%) from F_{best} , shown in Table 1. In the following analyses with FPAPA, switch probability values of $p_L = 0.2$ and $p_U = 0.8$ are assumed. Furthermore, a population size of $n = 10$ individuals is used for B1, B2 and of $n = 20$ for the other frames. Twenty independent trial runs are used for each frame to account for the stochastic nature of FPAPA.

Figure 4 presents the mean optimization histories of FPAPA for all benchmark RC frames and for three different step sizes (i.e. $\gamma = 0.1, 1.0$ and 10.0). It is first observed that all average histories converge practically to zero within a small number of evaluations. This is important since function evaluations are computationally expensive in RC frames design. As expected, optimization histories converge more rapidly for B1, B2 and less quickly for benchmarks B4-B6 due to the larger size of the latter search spaces. Nevertheless, in all cases, the optimization histories reach 2% errors in less than $70 \cdot d$ function evaluations, where d stands for the total

number of design variables. Figure 4 shows also that the step size γ does not greatly affect the convergence response. A step size of $\gamma = 1.0$ seems to offer the best response for the most challenging benchmark problem B6 and therefore is used in the rest of this study. By using $\gamma = 1.0$, FPAPA reaches on average 2% errors within only $40 \cdot d$ function evaluations for all benchmark problems.

Furthermore, Figures 5-7 compare the response of the FPAPA algorithm against the original FPA assuming two different p values (i.e. $p = 0.8$ & $p = 0.2$) that match the values of p_L and p_U assumed for FPAPA in this study. It is recalled that the FPAPA has been found to offer statistically significant improvements with respect to the original FPA when tested against the set of IEEE-CEC'13 [56] challenging and complex optimization problems [53].

Figure 5 compares the average convergence histories coming from 20 independent runs for each algorithm and for all benchmarks. It is noted that all algorithmic options offer similar convergence efficiency. This could be attributed to the rather simple landscape of the examined optimization problems for which the switch probability values of FPA seem to not influence significantly computational performance.

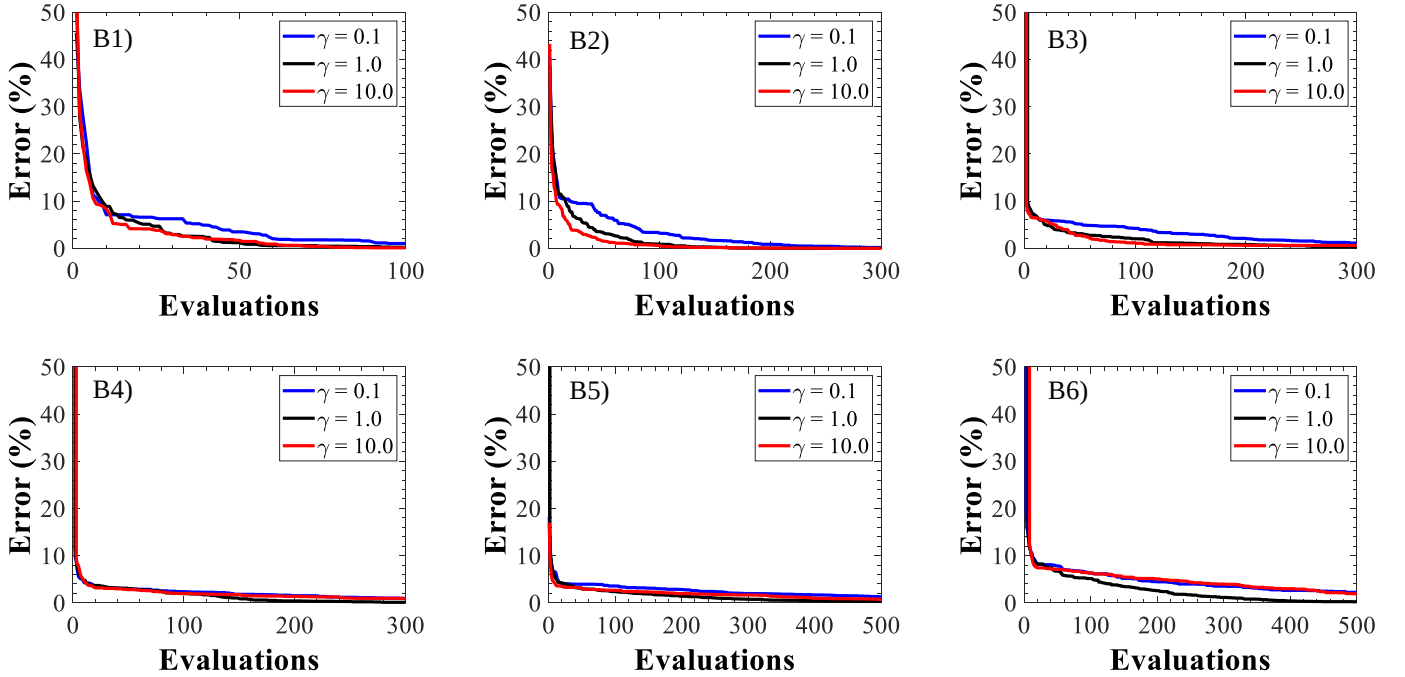


Figure 4: FPAPA average optimization histories with different step sizes

Furthermore, Figure 6 shows the box plots of function evaluations required to converge (i.e. success) to the global optima obtained by the different runs of the FPA variants. Successful runs are only shown in this therein. A run is treated as successful when the algorithm tracks the global best solution in less than 1000 function evaluations for all benchmarks problems

apart from B1, where only 100 function evaluations are used. The limit of 1000 evaluations is generally considered as a reasonable computational budget to afford for optimizing an RC frame in everyday practice. For B1, the limit of 100 function evaluations matches the size of the search space. Like in Figure 5, very small differences amongst the different algorithms are noticed in Figure 6. The total number of successes, out of 20, of all FPA variants and for all benchmark problems are presented in Figure 7. It is observed that marginally the FPA with $p = 0.2$ has a higher number of successes within the affordable computational budget. This could be partly explained by the increase in exploitation capacity of the FPA when the switch probability value decreases, but the differences are rather small to make solid conclusions.

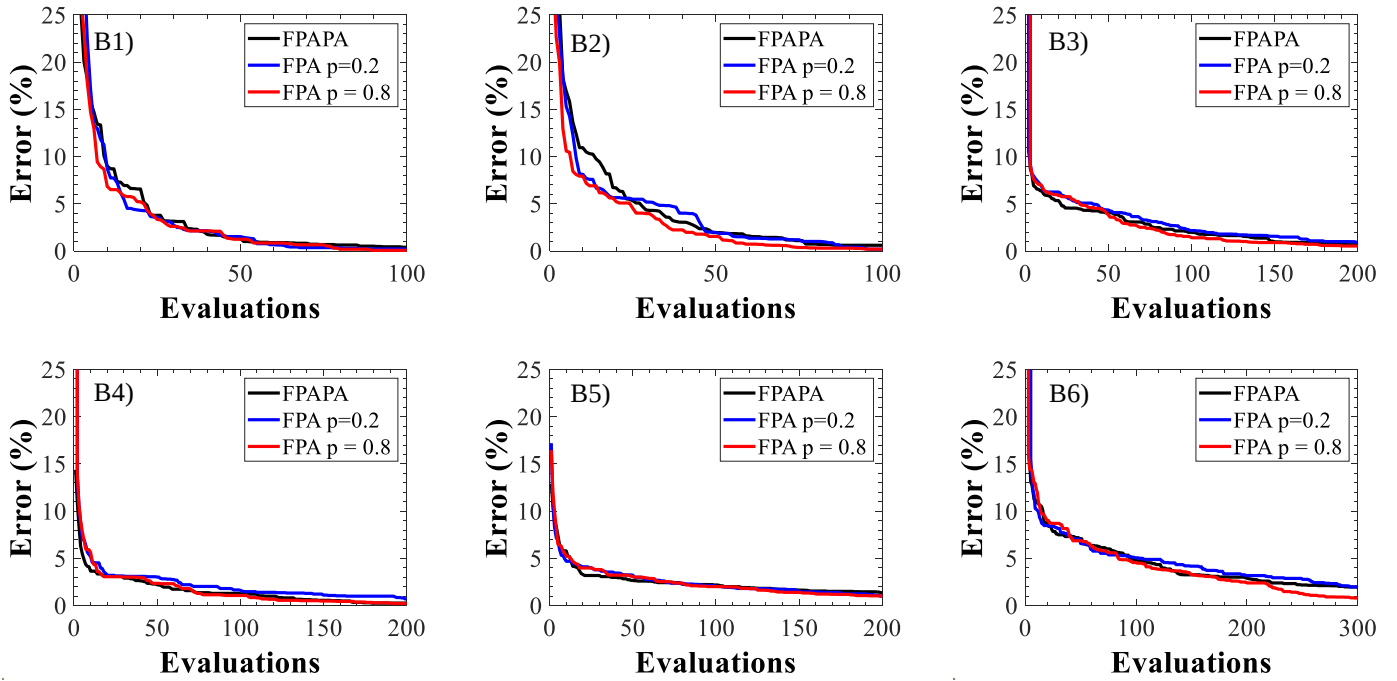
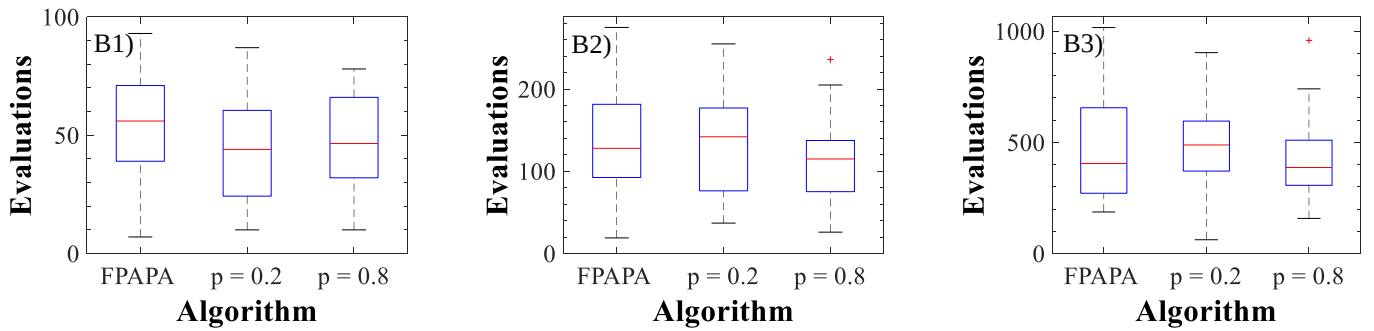


Figure 5: Average optimization histories of FPAPA and the original FPA with $p = 0.2$ and $p = 0.8$



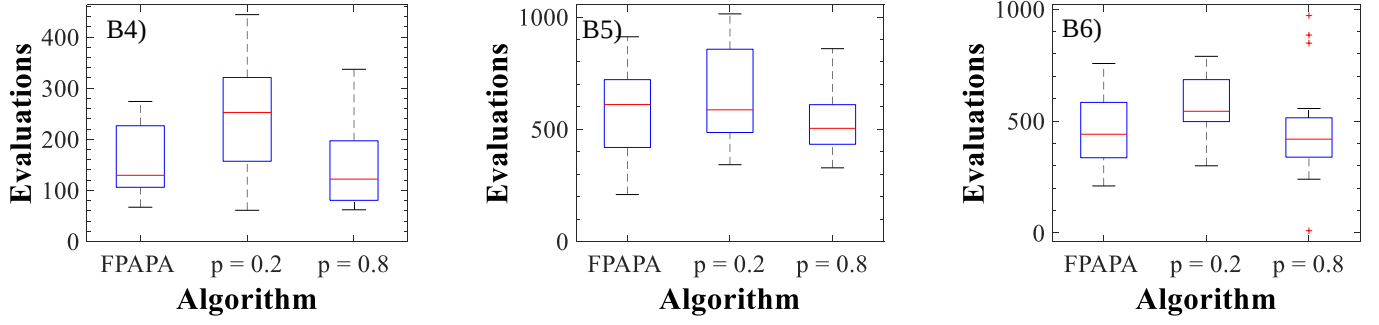


Figure 6: Number of function evaluations till reaching global optimum of FPAPA and the original FPA with $p = 0.2$ and $p = 0.8$

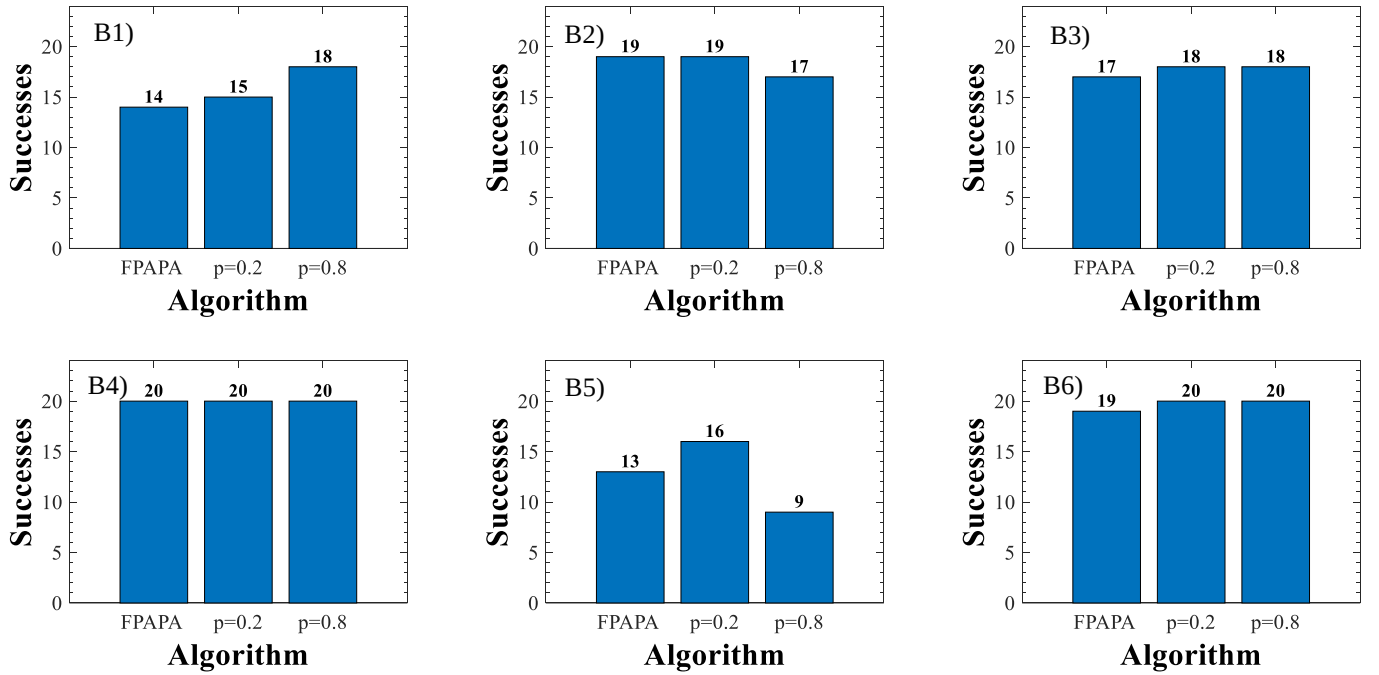


Figure 7: Number of runs reaching global optimum (i.e. successes) out of 20 of FPAPA and the original FPA with $p = 0.2$ and $p = 0.8$

Moreover, Figures 8-10 compare the performance of FPAPA against some of the most established evolutionary algorithms in literature lie the GA [8], SA [9] and PSO [10]. GA simulates Darwin's evolution theory. SA resembles the annealing process in metallurgy to evolve a candidate design solution. Finally, PSO is a famous evolutionary algorithm that takes inspiration from fish schools and bird flocks. It is noted that the SA, PSO and GA are formulated and implemented as described in [67]. Furthermore, the GA and PSO assume the same population sizes as FPAPA for the different benchmark problems herein. The rest of the algorithm parameters for GA, SA and PSO assume the default values recommended in [67] that seem to maximize their computational performance.

Figure 8 demonstrates the average optimization histories of the various algorithms out of 20 independent runs. It is seen that the PSO and SA tend to converge quicker for the small-scale optimization problems B1-B3, but they become slower for the larger scale problems B4-B6. The FPAPA algorithm exhibits similar convergence rates to GA for all benchmarks apart from B6, where the latter algorithm converges more rapidly. Furthermore, Figures 9 and 10 show the numbers of function evaluations required for tracking global optimum solutions (i.e. success) by all algorithms as well as the number of successes out of the 20 independent runs within the afore-described computational budget. It is observed that the PSO requires the smallest or second smallest numbers of function evaluations for tracking the global optima in Figure 9. This observation hints at the high exploitation ability of this algorithm. Nevertheless, in Figure 10, it is observed that the FPAPA and GA algorithms are more successful at tracking F_{best} than the SA and PSO algorithms for all benchmark problems apart from B1. This indicates that the former algorithms are more capable of exploring the search space than the latter. The high capability of the FPA algorithm and its variants to explore complex search landscapes is a common observation in many similar studies [e.g. 11, 27, 65].

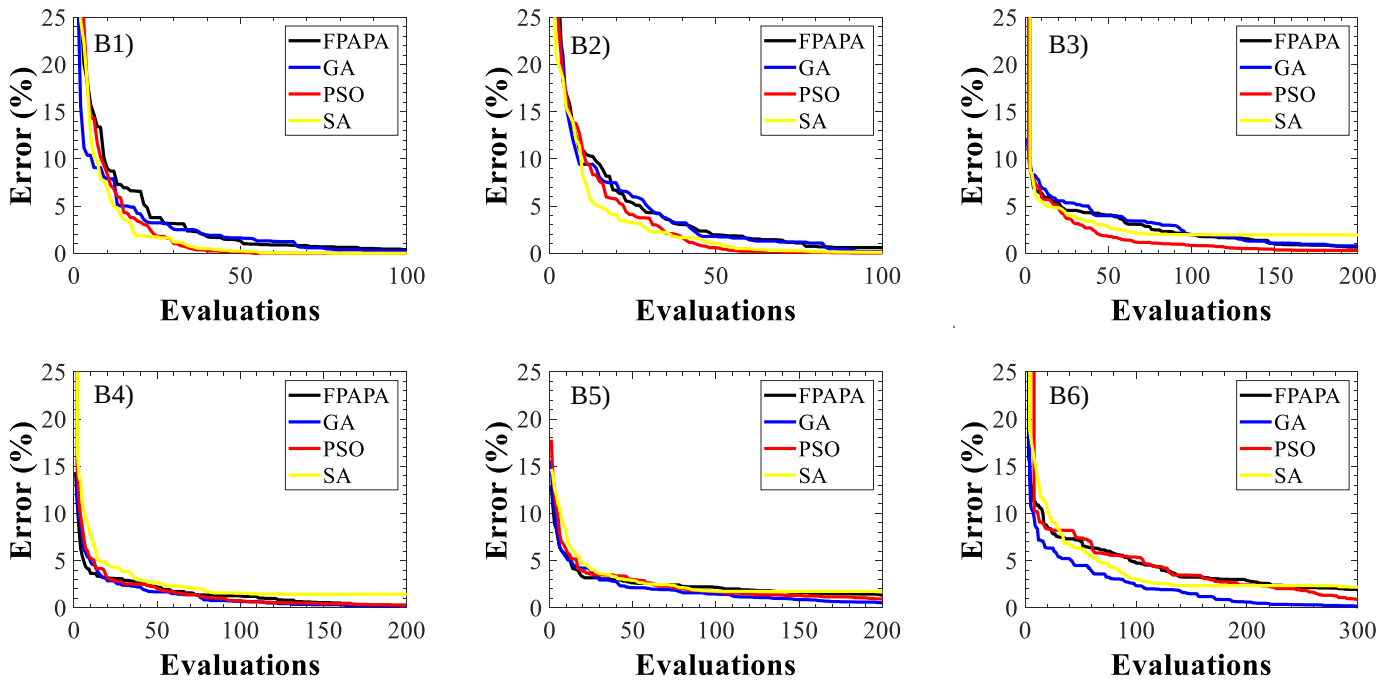


Figure 8: Average optimization histories of FPAPA and other algorithms

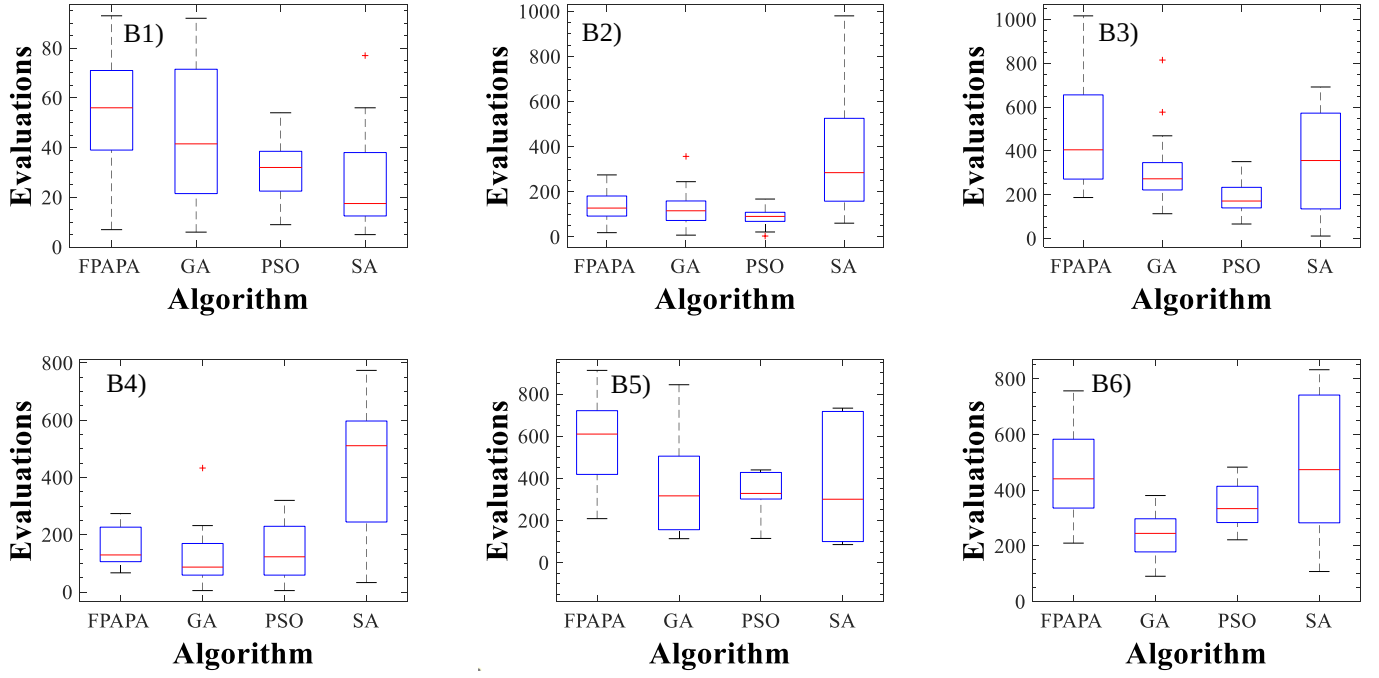


Figure 9: Number of function evaluations till reaching global optimum of FPAPA and other algorithms

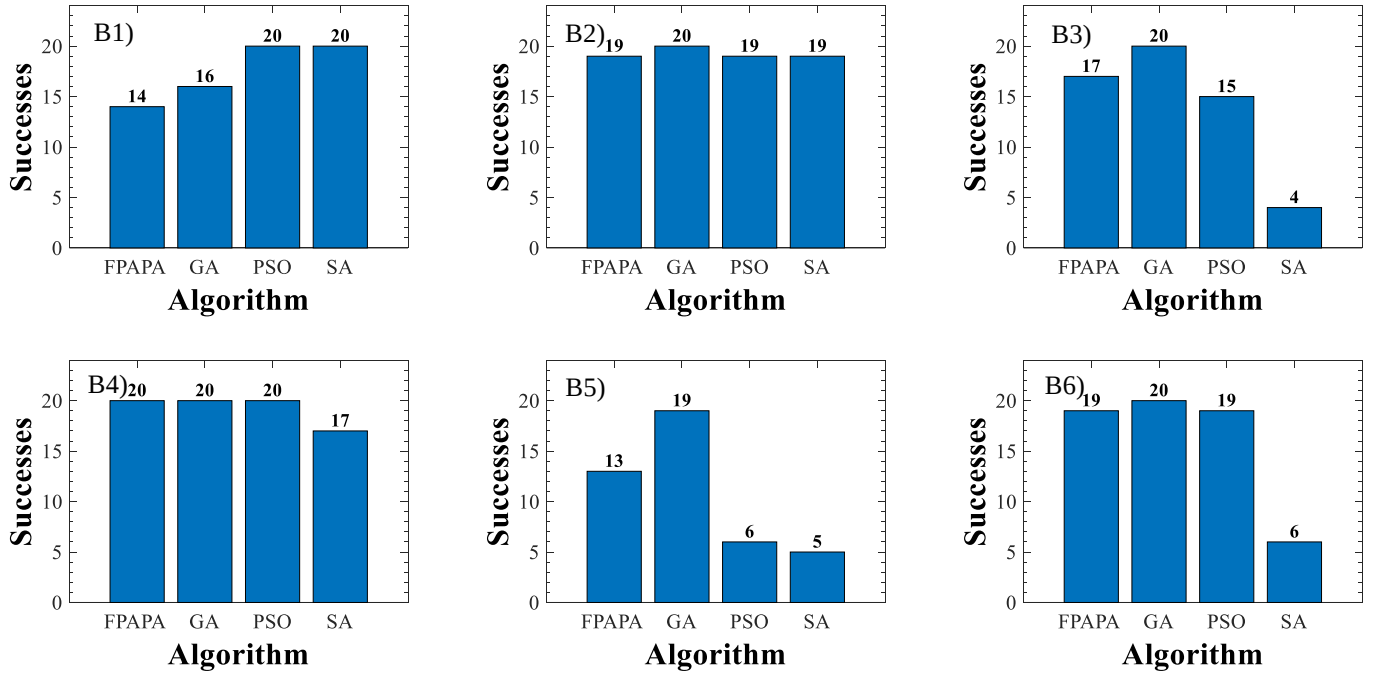


Figure 10: Number of runs reaching global optimum (i.e. successes) out of 20 of FPAPA and other algorithms

6 Conclusions

Optimum structural design of RC frames represents an important challenge in the road of decarbonising the built environment. Due to the complex nature of this design problem, computationally efficient optimization algorithms are required. FPA is one of the most competitive metaheuristic algorithms imitating the successful reproduction process of flowers on earth. In this study, a novel FPA variant is examined, named FPAPA, that accounts for a new evolutionary feature in the natural pollination process called Pollinator Attraction. This evolutionary characteristic describes the fact that flowers evolve to become more attractive to pollinators and thereby achieve reproduction by biotic pollination. Consistently, FPAPA provides fitter flowers with a higher probability of conducting biotic pollination that is a global search mechanism. FPAPA has been found to offer statistically significant improvements to the original FPA when applied to complex and multimodal objective functions.

In the present study, FPAPA is applied to the structural optimization of concrete frames. More specifically, the performance of FPAPA is tested against a set of six benchmark structural optimization problems of concrete frames with known global optimum solutions. It is found that FPAPA manages to track near global optima within a computational budget that could be easily afforded in standard engineering practice. In this category of optimization tasks, FPAPA seems to offer similar computational efficiency to the original FPA algorithm. Furthermore, comparisons with other well-established optimization algorithms, show that FPAPA offers competitive convergence rates and more robust performance at tracking global optimum solutions.

Closing this chapter, it is recommended that further studies investigate the efficiency of FPAPA and other alternative algorithms in the structural optimization of large-scale and complex real-world RC frames with numerous design variables.

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