Available online at www.eccomasproceedia.org
Eccomas Proceedia COMPDYN (2025) 494- 505

ECCOMAS
Proceedia

COMPDYN 2025
10th ECCOMAS Thematic Conference on
Computational Methods in Structural Dynamics and Earthquake Engineering
M. Papadrakakis, M. Fragiadakis (eds.)
Rhodes Island, Greece, 15-18 June 2025

EVALUATION OF CLUSTER-BASED AND RANDOM RECORD ASSIGNMENT HEURISTICS TO OPTIMIZE DAMPER DISTRIBUTIONS IN BUILDINGS SUBJECTED TO EARTHQUAKES

Oscar Contreras-Bejarano[1], Diego Lopez-Garcia[2], Jesús D. Villalba-Morales[3], and Dario De Domenico[4]

[1] Department of Structural and Geotechnical Engineering, Pontificia Universidad Catolica de Chile
Av. Vicuña Mackenna 4860 Macul, Santiago, Chile
e-mail: contreras1@uc.cl

[2] Department of Structural and Geotechnical Engineering, Pontificia Universidad Catolica de Chile & Research Center for Integrated Disaster Risk Management (CIGIDEN) ANID FONDAP 1523A0009
Av. Vicuña Mackenna 4860 Macul, Santiago, Chile
e-mail: dlg@uc.cl

[3] Department of Civil Engineering, Pontificia Universidad Javeriana
Cra 7 No 40 – 62, Bogotá, Colombia
e-mail: jesus.villalba@javeriana.edu.co

[4] Department of Engineering, Università degli Studi di Messina,
Contrada Di Dio, Villaggio S. Agata, 98166, Messina, Italy
e-mail: dario.dedomenico@unime.it

Abstract

Two variations of bio-inspired, population-based optimization frameworks are proposed to optimize damper distributions in structures subjected to earthquakes. In the first approach a predefined number of records are randomly selected and assigned to each individual of the population. The second approach consists of clustering individuals with similar characteristics, and each individual of each cluster is subjected to just a few randomly selected ground motions. The proposed variations are applied to an archetype building model subjected to different sets of ground motions caused by different types of earthquakes (shallow crustal and subduction). It was found that the clustering approach is much more convenient in the sense that it reduces the computational cost without significantly affecting the quality of the solution.

Keywords: Differential Evolution Algorithm, Optimization, Viscous Dampers, Heuristics.

doi: 10.7712/120125.12669.25065

1 INTRODUCTION

Viscous dampers are important components of seismic protection systems and have the potential to mitigate adverse structural performance during earthquakes. Various optimization algorithms can be applied to determine optimal spatial distributions of damper properties. However, these algorithms often involve significant Computational Costs (CCs) [1], This challenge is particularly evident in population-based optimization algorithms, where the simultaneous evaluation of multiple solutions is necessary [2].

The seismic hazard is typically represented by several Ground Motions (GMs) to ensure statistical representativeness of the seismicity of interest. Ideally, the structural analyses performed as part of the optimization process should consider the entire set of GMs [3]. However, this approach is often computationally infeasible. To address this issue, Lavan and Levy [4] proposed a methodology to reduce the CC that consists of selecting the GM that has the largest spectral displacement at the natural period of the structure. The optimization process is then applied using only this GM. Once an optimal solution is identified, it is validated using the remaining GMs. If the solution fails to meet the constraints for some GMs, the optimization process is repeated using the GMs for which the constraints were violated. This iterative process continues until an optimal solution satisfies all the constraints for the entire set of GMs. Apostolakis and Dargush [5] selected 25 GMs representing earthquakes with a 5% probability of exceedance in 50 years (severe earthquakes). From this set, four GMs were selected for the optimization process based on the largest interstory drift and floor acceleration responses observed in 3- and 6-story moment-resisting frames. A population-based optimization algorithm was applied. Similarly, Nabid et al. [6] proposed an approach that uses 6 synthetic GMs compatible with the European Code (EC8) design spectrum. The optimization was performed using a single synthetic GM and the remaining GMs were used to assess the sensibility of the optimal solution. Likewise, De Domenico and Hajirasouliha [7] introduced a design methodology that uses a single synthetic response-spectrum-compatible GM, which generally produced acceptable results for low- and medium-rise structures. Additionally, Fang et al. [8] selected real GMs based on parameters such as pulse and magnitude. To reduce the CC, a random GM was used during the optimization process in a population-based algorithm. Other strategies to mitigate the CC include Endurance Time analysis [9] [10] and parallel computing techniques [11].

The determination of the optimal properties of viscous dampers in buildings subjected to earthquakes is a multimodal optimization challenge. Consequently, optimization algorithms may become trapped in local optima. In population-based bio-inspired algorithms this issue can be addressed through the application of diversity conservation techniques. Differential Evolution (DE), a bio-inspired optimization algorithm, employs a fast and robust stochastic parallel search strategy. This approach can effectively address multimodal and nonlinear objective functions [12].

This paper presents an alternative approach to reduce the CC of a DE optimization process through clustering techniques. Section 2 outlines the formulation of the optimization problem. Section 3 describes the proposed methodology. Finally, Sections 4 and 5 present the results and conclusions, respectively.

2 DIFFERENTIAL EVOLUTION ALGORITHM FOR SEISMIC OPTIMIZATION

Optimization algorithms are structured around an objective function. The operators of the algorithm iteratively refine candidate solutions to achieve optimality. In this study, the optimization problem focuses on the determination of the optimal properties of supplemental viscous dampers in structures subjected to earthquakes, optimal in the sense that the response is as close as possible to a target response. The problem is analyzed considering two different Objective Functions (OFs). The first OF is given by:

$$OF_1 = ln\left(\left|\Delta_{target}^{norm} - \Delta_i^{norm}\right|\right) \tag{1}$$

where:

$$\Delta_{target}^{norm} = \frac{\Delta_{target} - \Delta_{min}}{\Delta_{max} - \Delta_{min}} \tag{2}$$

$$\Delta_i^{norm} = \frac{\Delta_i - \Delta_{min}}{\Delta_{max} - \Delta_{min}} \tag{3}$$

where, in turn, Δ_{target} is the target interstory drift response, Δ_{min} is the peak interstory drift response (over all stories) of the structure equipped with the upper bound amount of supplemental damping considered in this study (first-mode supplemental damping = 30%, uniform height-wise damper distribution), Δ_{max} is the peak interstory drift response (over all stories) of the structure with no supplemental damping, and Δ_i is the peak interstory drift response (over all stories) of the structure equipped with a given set of supplemental dampers (i.e., a candidate solution). The second OF is given by:

$$OF_2 = \left|\Delta_{target}^{norm} - \Delta_i^{norm}\right| + \sqrt{\frac{\sum_{l=1}^{ns}\left(C_{d_{i_l}}^{norm} - \overline{C_{d_l}^{norm}}\right)^2}{ns}} \tag{4}$$

where:

$$\overline{C_{d_i}^{norm}} = \frac{1}{ns}\sum_{l=1}^{ns} C_{d_{i_l}}^{norm} \tag{5}$$

$$C_{d_{i_l}}^{norm} = \left[\frac{C_{d_{i_l}} - C_{d_{min}}}{C_{d_{max}} - C_{d_{min}}}\right] \tag{6}$$

where, in turn, $C_{d_{i_l}}$ is the l-th story damper coefficient of the structure equipped with a given set of supplemental dampers (i.e., a candidate solution), $C_{d_{min}}$ is the lower bound of the damping coefficient of the dampers (= 0 in this study), $C_{d_{max}}$ is the upper bound of the damping coefficient of the dampers (as mentioned before, first-mode supplemental damping = 30% when the damper coefficient is $C_{d_{max}}$ at all stories), and ns is the number of stories.

The OF_1 is defined solely in terms of the structural response, and (as it will be shown later) the natural logarithm was introduced to more clearly identify the best solutions. The OF_2 is defined in such a way that uniform height-wise damper distributions are preferred over non-uniform distributions, which is an important practical consideration. The normalized quantities defined in Equations 2-3 and 5-6 make the 2 terms of Equation 4 (i.e., the OF_2) dimensionless and comparable to each other, which is necessary to ensure that both criteria of interest (structural response and uniformity of the damper distribution) are equally accounted for in the optimization process.

To find the most effective damping distribution, this study applies a metaheuristic approach based on DE, where the structure equipped with a given damper distribution is referred to as an individual, and a set of individuals is referred to as population. The performance of each individual is evaluated based on its structural response, referred to as its fitness. The search space consists of all possible damper distributions. Mutation, crossover and selection are evolutionary operators used to explore the search space in pursuit of optimal solutions. The optimization process starts with the generation of a random set of individuals, known as the initial population. The fitness of each individual is evaluated based on its structural response. In DE, mutation and crossover are critical stages for the generation of new solutions. These stages depend on the fitness of high-quality individuals, which influences the development of a new set of solutions known as the trial population. The selection process consists of comparisons between the fitness of individuals of the initial population with those of the trial population. The best-performing individuals from both populations are combined to form the target population. Mutation and crossover are then applied to the target population to generate a new trial population, which is subsequently evaluated to identify the best solutions. This iterative process, referred to as a generation, is repeated until an optimal solution is achieved.

3 METHODOLOGY

The optimization procedure is applied to a 6-story structure equipped with supplemental viscous dampers and subjected to 3 sets of GMs. The structure is modeled as a 2D lumped-mass shear building. The floor mass is 120 tons at all floors and the fundamental period is 1.0 s. The stiffness of a given story is 95% of the stiffness of the story immediately below. The damping coefficients of the dampers range from 0 to 6000 (kN s)/m (i.e., $C_{d_{min}}$ = 0 and $C_{d_{max}}$ = 6000 (kN s)/m), with increments of 1500 (kN s)/m (i.e., 5 possible values).

Figure 1 presents the response spectra of the 3 sets of GMs. In all cases the target spectrum is the design spectrum defined by the Chilean seismic design code NCh 433 for structures located in Seismic Zone 2 on Soil Type B. The importance factor was assumed equal to unity (residential buildings). Each GM of the first two sets was scaled in such a way that the spectral ordinate at the fundamental period of the structure matches the spectral ordinate of the target spectrum. The GMs of the third set were scaled in such a way that the mean spectrum of the scaled GMs matches the target spectrum in the 0.0 s – 4.0 s range.

The optimization algorithm integrates two heuristics to reduce the CC. Both heuristics modify the assignment of GMs to individuals of the population (i.e., each individual is subjected only to the GMs assigned to it). In the standard approach all GMs are assigned to each individual, which requires high computational resources. The heuristics evaluated in this study aim to reduce the CC while preserving the quality of the optimal solution. Figure 2 outlines the operation of these heuristics:

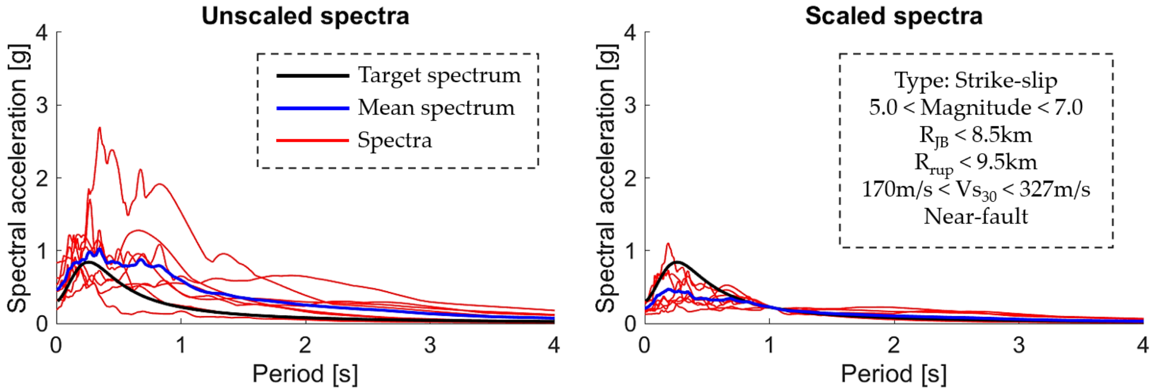
- **Heuristic 1**: Assigns n random GMs to each individual, where n is less than the number of GMs of the set.
- **Heuristic 2**: Individuals are grouped into n_c clusters based on the similarity of their damping distributions. Each cluster is assigned to the entire set of GMs, which are then randomly distributed among the individuals of the cluster. The number of clusters n_c does not exceed half the total number of individuals. If a cluster contains more individuals than GMs, at least one GM is assigned to more than one individual.

The CC of these heuristics is evaluated in terms of the number of response history analyses, and is given by the following expressions:

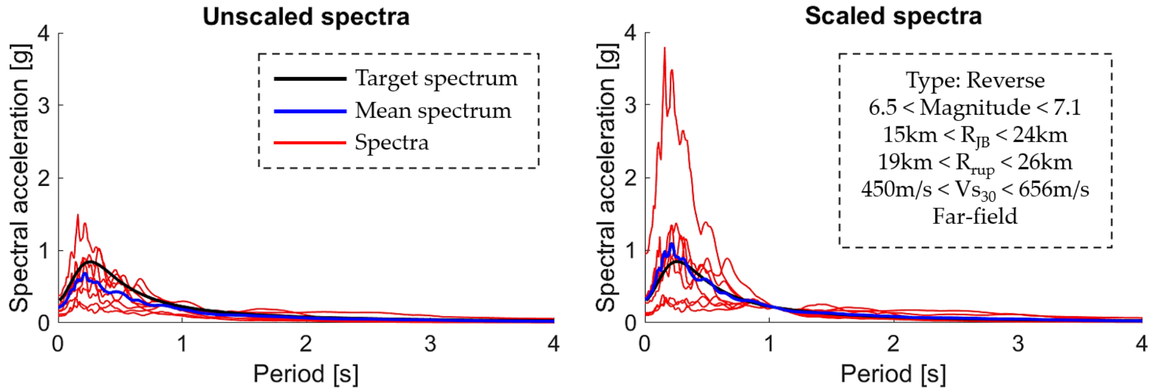
- Standard approach: $CC = NGM\ NI\ N_{gen}$, where NGM is the number of GMs, NI is the number of individuals, and N_{gen} is the number of generations.
- Heuristic 1: $CC = n\ NI\ N_{gen}$,
- Heuristic 2: The number of individuals per cluster cannot be predetermined due to the randomness in metaheuristic optimization algorithms. Therefore, the CC depends on the sum of analyses over all clusters. The exact cost varies with the number of individuals of each cluster and follows the expressions in Equations (7) and (8).

$$CC = \sum_{j=1}^{N_{gen}} \sum_{i=1}^{n_c} \beta_{j,i} \tag{7}$$

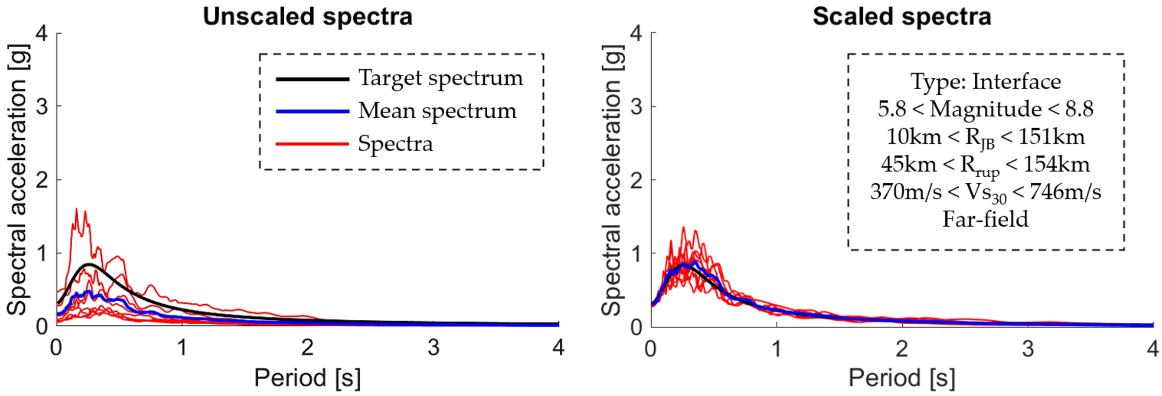
$$\beta_{j,i} = \begin{cases} NGM & if \quad NI_i \leq NGM \\ NI_i & if \quad NI_i > NGM \end{cases} \quad , \quad i = 1, 2, \dots, n_c \tag{8}$$



(a)



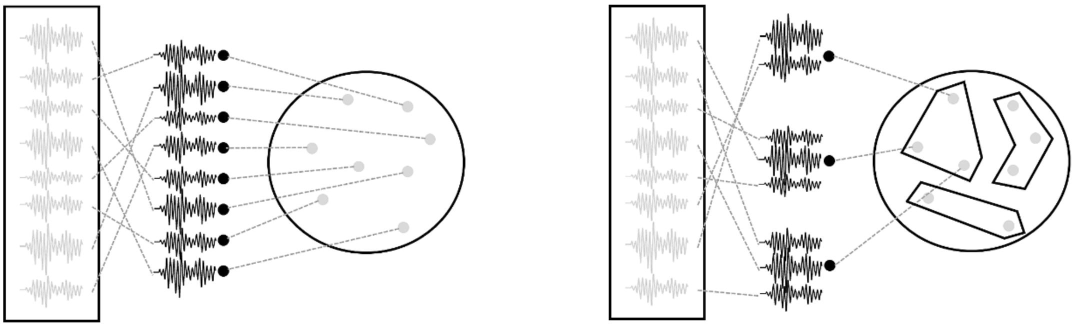
(b)



(c)

Figure 1. Ground motion spectra: (a) 8 near-fault shallow crustal records (set 1); (b) 8 far-field shallow crustal records (set 2); (c) 8 subduction records (set 3)

Three values of n and n_c were tested, as summarized in Table 1. Additionally, an exhaustive search method was conducted to establish a benchmark for comparisons. The initial population was generated randomly. To balance exploration and exploitation in the optimization process, a parameter control technique based on the Lévy probability distribution [13] was applied. A diversity conservation technique was used during selection, including comparisons between most similar neighboring individuals to prevent premature convergence to local optima. Additionally, a constraint related to the exceedance of the target response was introduced and evaluated using static penalization. In all cases, NI was set to 30 and N_{Gen} was set to 400.



(a) (b)

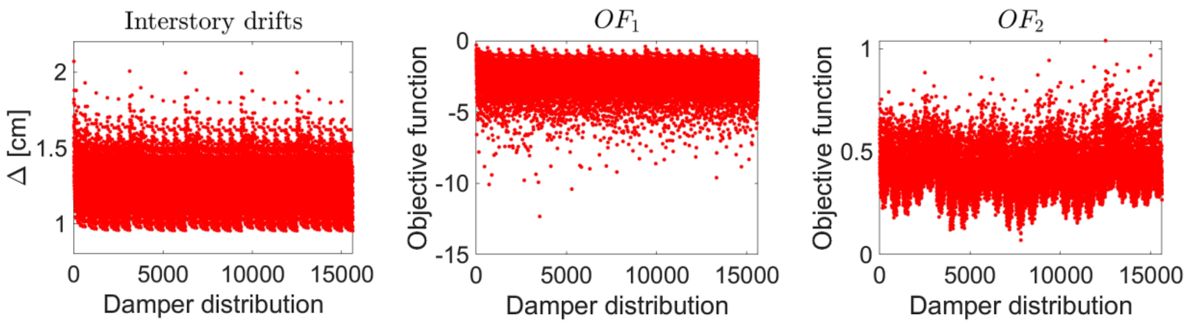
Figure 2. Alternative assignments of GMs. (a) Heuristic 1 with n = 1. (b) Heuristic 2 with n_c = 3

GMs	Heuristic 1 (n)			Heuristic 2 (n_c)		
Set 1	2	4	6	5	10	15
Set 2	2	4	6	5	10	15
Set 3	2	4	6	5	10	15

Table 1. Values of the Heuristics

4 RESULTS AND DISCUSSION

Results obtained considering each combination of GM set and heuristic approach (Table 1) were compared with the global optimum results, which were obtained through exhaustive search. Figure 3(a) presents the interstory drift response to the GM set 1 considering all the possible damper distributions, i.e., exhaustive search (5^6 = 15625 distributions). The target interstory drift was set equal to 1.25 cm. Figure 3(a) suggests that there are several damper distributions that give the target interstory drift (i.e., several solutions). Figure 3(b–c) depict the values of the quantities OF_1 and OF_2 (Equations 1 and 4) of the 15625 distributions. The true global optimal solutions can now be clearly identified, along with several other near-optimal solutions.



(a) (b) (c)

Figure 3. Exhaustive search analyses, GM set 1. (a) Interstory drift response. (b) Objective Function 1. (c) Objective Function 2.

Figure 4(a) presents the best 64 solutions based on OF_1. The interstory drift response of all of them is very similar to the target response (in fact identical if the interstory drift response, in cm, is rounded to 2 decimal places). The values of OF_2 of these 64 solutions are shown in Figure 4(b). A comparison between Figure 3(c) and Figure 4(b) clearly shows that none of the best 64 solutions based on OF_1 is the optimal solution based on OF_2.

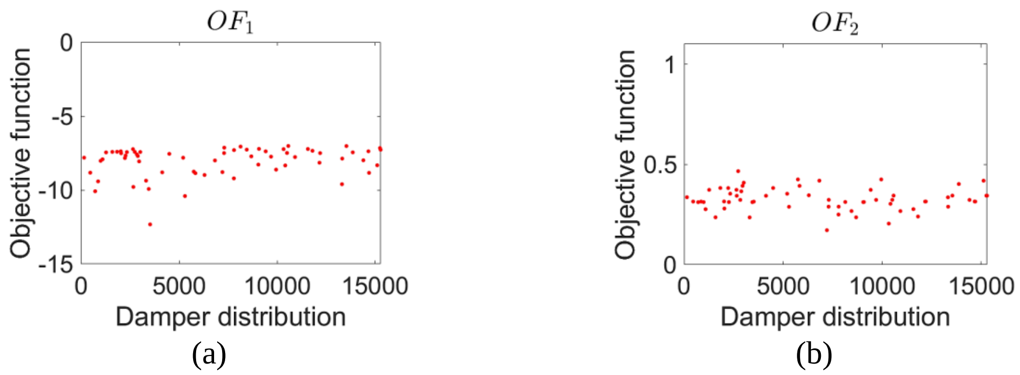


Figure 4. Best 64 solutions based solely on the value of the OF_1, GM set 1. (a) Values of OF_1. (b) Values of OF_2.

Figure 5(a–b) presents the optimal damping coefficients (i.e., the optimal solutions) for both objective functions and for the 3 GM sets. The optimal solution for OF_1 is different for each GM set, and the damping distribution of these solutions is far from uniform (i.e., the optimality criterion is based solely on the interstory drift response). In contrast, the optimal solution for OF_2 is the same regardless of the GM set, and is a uniform distribution (i.e., the optimality criterion also accounts for uniformity in the damper distribution). Further insight is provided in Figure 6, which shows the interstory drift response of each of the optimal solutions shown in Figure 5(a–b).

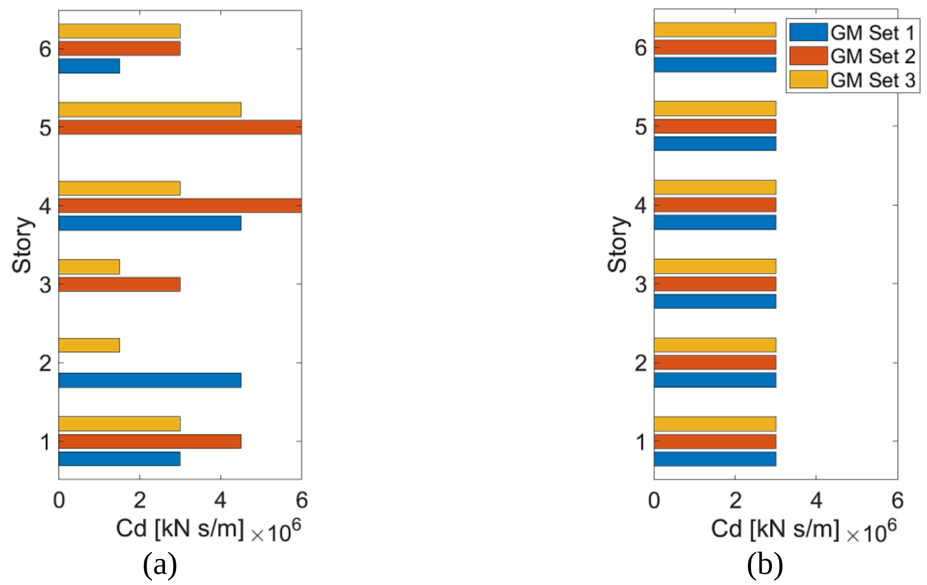


Figure 5. Optimal damping coefficients (i.e., optimal solutions)

The response of the OF_1 optimal solutions is exactly equal to the target response, whereas the response of the OF_2 optimal solutions are not exactly equal to the target response but somewhat smaller. In other words, uniformity is achieved at the expense of a somewhat smaller structural response.

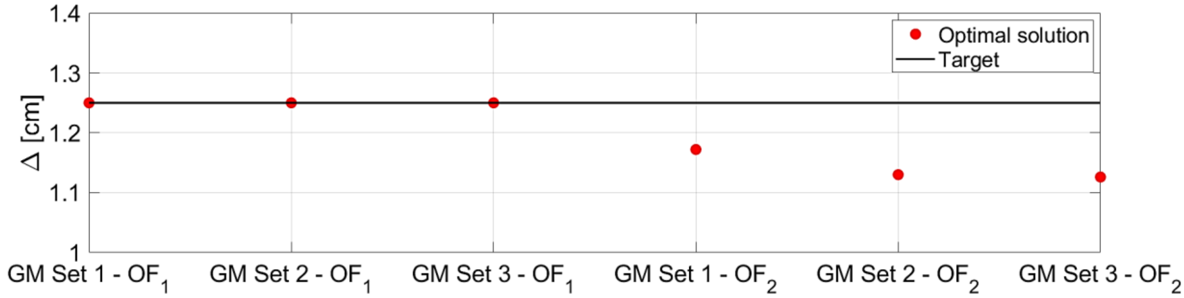


Figure 6. Interstory drift response of the optimal solutions

Next, results obtained with the DE optimization algorithm adopted in this study (with and without the heuristics described before) are presented and analyzed. It is recalled that the heuristics proposed in this study aim to reduce the CC, ideally without compromising the quality of the solution. Figure 7(a–b) present examples of convergence plots of the DE algorithm with Heuristics 1 and 2, respectively, where convergence occurs before 200 generations. The maximum number of generations (= 400) and the population size (= 30) were determined based on the number of analyses performed in the exhaustive search.

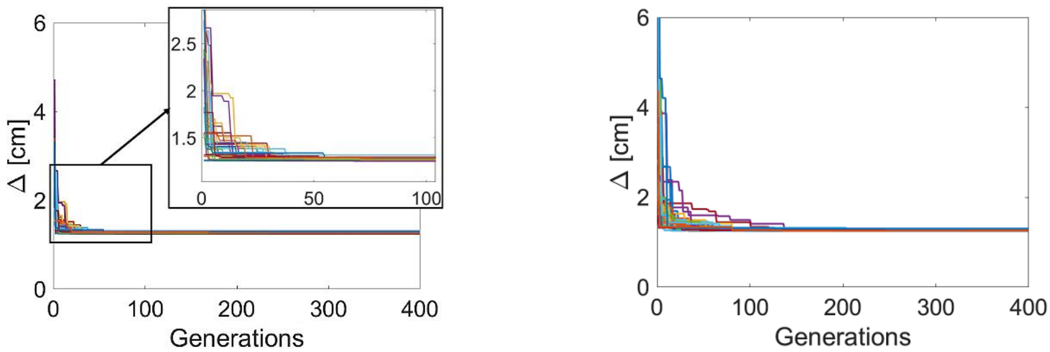


Figure 7. Convergence plots of the DE algorithm, GM set 1 and OF_1. (a) Heuristic 1, n = 2. (b) Heuristic 2, n_c = 5

It must be noted that the initial population may be subject to penalty factors due to constraint violations, which intentionally increase the value of the interstory drift response. As a result, the interstory drift response of the first generations is typically much larger than that at convergence.

When the DE is applied without heuristics all individuals are evaluated using the complete set of GMs. In contrast, when the heuristics are applied, each individual is evaluated using a variable number of randomly selected GMs. If the structural response to the full set of GMs differs from that evaluated with randomly selected GMs, then a bias is introduced into the optimization process. In this context, two types of responses are defined: apparent interstory drift response, obtained directly from the optimization process with heuristics; and real interstory drift response, which is obtained by evaluating the optimal solution (obtained with heuristics) using the complete set of GMs.

Figure 8(a–f) presents the values of the two types of response (apparent and real) for all the heuristics and GM sets considered in this study. It must be noted that the case denoted as n = 8 is in fact the case where the DE algorithm is applied without heuristics (i.e., the standard approach defined before) Notably, when the objective function is OF_1 the apparent response is essentially identical to the target response, which demonstrates that the DE algorithm explores the search space effectively and identifies an optimal solution. In contrast, when the objective function is OF_2 the apparent response is not exactly equal to the target response because, as explained before, uniformity is achieved at the expense of a response that is somewhat different from the target. It must be noted that the apparent response is always equal to or smaller than the target (i.e., it is never larger than the target), which is due to penalizations included in the optimization algorithm.

The difference between real and apparent responses is indicative of the quality of the solution obtained with the heuristics, i.e., the smaller the difference the higher the quality of the solution with heuristics (ideally the difference should be zero). Obviously, when n = 8 (i.e., no heuristics) the apparent response always coincides with the real response. It can be observed that the real and apparent responses do not coincide in many cases. It can also be observed, however, that Heuristic 2 (i.e., n_c = 5, 10 and 15) always gives apparent responses that are much closer to the real ones than those given by Heuristic 1. In other words, Heuristic 2 gives better solutions than Heuristic 1. Finally, it is also observed that the relationship between the value of n_c and the difference between real and apparent responses is not consistently monotonic.

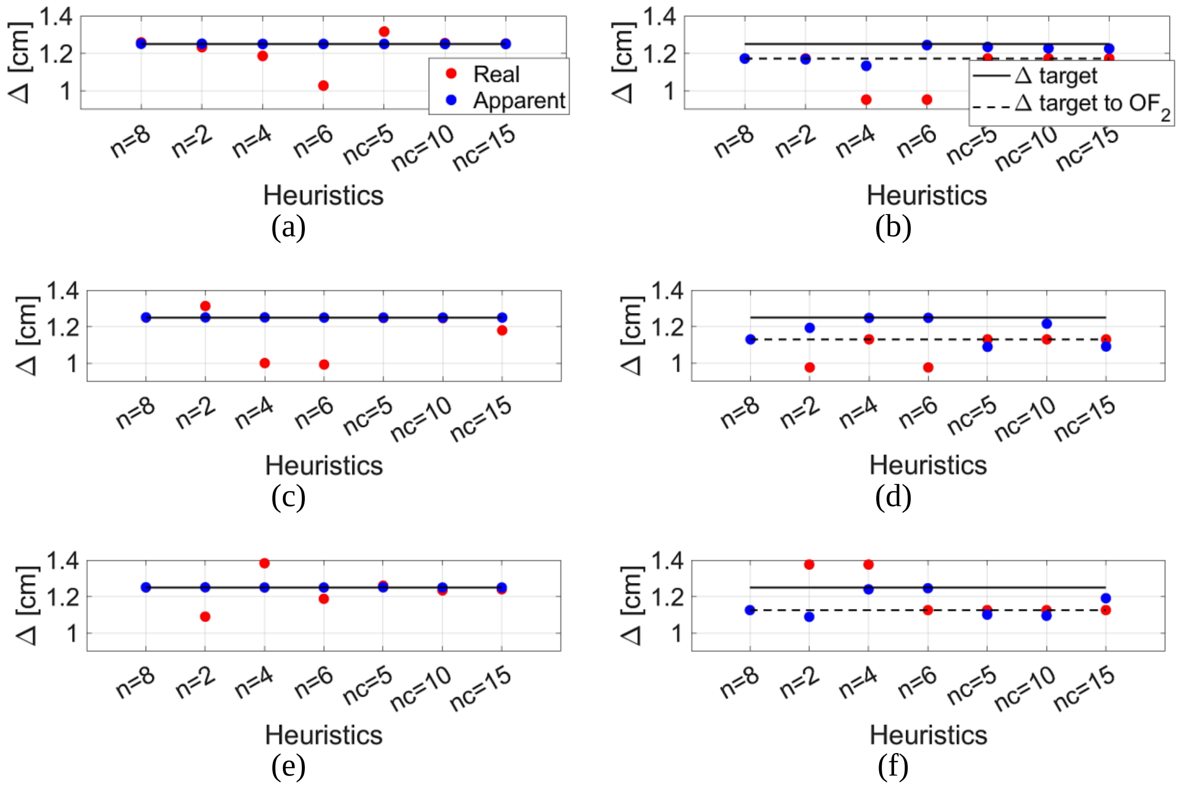


Figure 8. Apparent and real interstory drift response. (a) GM set 1 – OF_1. (b) GM set 1 – OF_2. (c) GM set 2 – OF_1. (d) GM set 2 – OF_2. (e) GM set 3 – OF_1. (f) GM set 3 – OF_2.

Figure 9 presents the values of two metrics to evaluate the performance of the heuristics. The first metric is the dispersion of the real responses with respect to the target response. This metric clearly shows that Heuristic 2 is much more reliable than Heuristic 1. The second metric is the CC, measured (as mentioned before) in terms of the number of response history analyses. It can be observed that Heuristic 2 decreases the CC (with respect to the standard approach) by at least 50%.

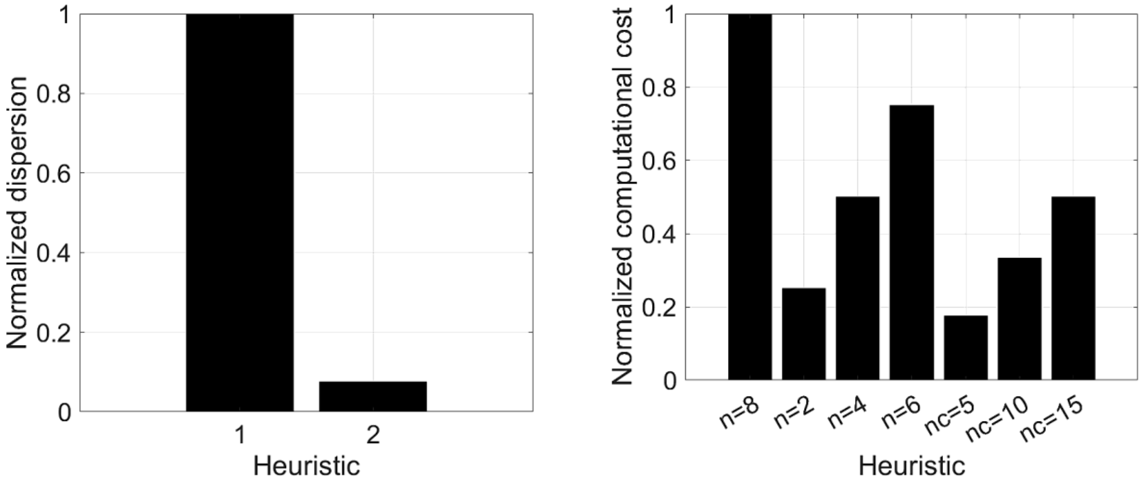


Figure 9. Metrics of the heuristics. (a) Dispersion of real responses. (b) Computational cost.

It is important to note that the computational *time* depends on the duration of the GMs. The duration of the shallow crustal GMs of sets 1 and 2 is significantly smaller than that of the GMs of set 3. Hence, while the number of analyses was the same regardless of the GM set, the computational time demanded by the GM set 3 was much larger than that demanded by the GM sets 1 and 2. Figure 10 shows the average computational time per execution for each heuristic in a high-performance computing cluster with 768 GB RAM, 10 parallel cores, and 10 Gbps Ethernet communication. Results indicate that Heuristic 2 requires significantly less computational time than Heuristic 1. In particular, Heuristic 2 with n_c = 5 took (on average) 2.28 hours, whereas the standard approach (i.e., n = 8), took 10.56 hours. This observation highlights the efficiency of Heuristic 2 in reducing computational cost.

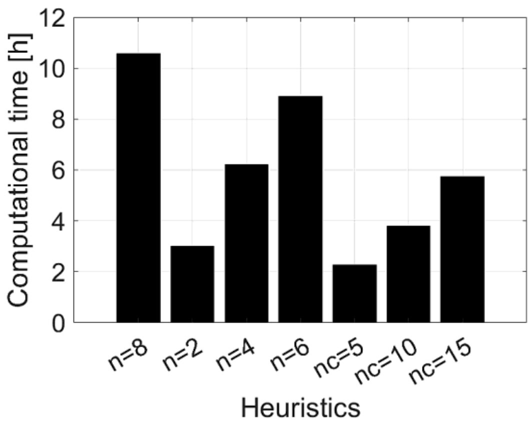


Figure 10. Comparison of computational times

Nevertheless, future research on alternative approaches to reduce the computational *time*, such as statistical prediction techniques, is recommended.

5 CONCLUSION

In this paper, 2 heuristics aimed at reducing the computational cost of Differential Evolution optimization algorithms were evaluated. The optimization algorithm was implemented with and without the heuristics to find the optimal distribution of viscous dampers in a building subjected to sets of ground motions. Heuristic 1 consists of random assignment of a pre-defined number of ground motions to each candidate solution. In Heuristic 2 similar candidate solutions are grouped into a pre-defined number of clusters, and the ground motions are randomly assigned to each cluster. Two objective functions were defined, and three different sets of ground motions were considered. Different values of the parameters of the heuristics were evaluated.

It was found that the optimization algorithm implemented without heuristics is indeed robust in the sense that it does find optimal solutions. It was also found that, as expected, the heuristics significantly reduce the computational cost, but at the expense of solutions that are sometimes not truly optimal. Heuristic 2 was found much preferable to Heuristic 1 because its effects on the quality of the solutions are much smaller. However, no clear relationship was found between the quality of the solutions given by Heuristic 2 and the number of clusters.

It is expected that Heuristic 2 proposed in this paper can be applicable to other optimization problems related to structural/earthquake engineering.

REFERENCES

[1] I. Takewaki, H. Akehashi, Comprehensive review of optimal and smart design of nonlinear building structures with and without passive dampers subjected to earthquake loading. *Frontiers in Built Environment*, **7**, 2021.

[2] D. De Domenico, G. Ricciardi, I. Takewaki, Design strategies of viscous dampers for seismic protection of building structures: A review. *Soil Dynamics and Earthquake Engineering*, **118**, 144–165, 2019.

[3] N. Pollini. Fail-safe optimization of viscous dampers for seismic retrofitting, *Earthquake Engineering & Structural Dynamics*, **49**, 1599–1618, 2020.

[4] O. Lavan, R. Levy, Optimal design of supplemental viscous dampers for irregular shear-frames in the presence of yielding. *Earthquake Engineering & Structural Dynamics*, **34**, 889–907, 2005.

[5] G. Apostolakis, G. F. Dargush, Optimal seismic design of moment-resisting steel frames with hysteretic passive devices. *Earthquake Engineering & Structural Dynamics*, **39**, 355–376, 2010.

[6] N. Nabid, I. Hajirasouliha, M. Petkovski, Adaptive low computational cost optimisation method for performance-based seismic design of friction dampers. *Engineering Structures*, **198**, 2019.

[7] D. De Domenico, I. Hajirasouliha, Multi-level performance-based design optimisation of steel frames with nonlinear viscous dampers. *Bulletin of Earthquake Engineering*, **19,** 5015–5049, 2021.

[8] C. Fang, Y. Ping, Y. Gao, Y. Zheng, Y. Chen, Machine learning-aided multi-objective optimization of structures with hybrid braces – Framework and case study. *Engineering Structures*, **269**, 2022.

[9] N. Ahadzadeh Kolour, M. Charkhtab Basim, M. Chenaghlou, Multi-objective optimum design of nonlinear viscous dampers in steel structures based on life cycle cost. *Structures*, **34**, 3776–3788, 2021.

[10] M. Karami, H. E. Estekanchi, I. Hajirasouliha, S. A. Mirfarhadi, Value-based seismic performance optimization of steel frames equipped with viscous dampers. *Journal of Earthquake Engineering*, **27**, 4024–4050, 2023.

[11] M. Baei, V. Terzic, Optimal design of dampers in seismic applications utilizing the MOPSO algorithm. *Frontiers in Built Environment*, **8**, 2022.

[12] E. Aydin, B. Ozturk, A. Bogdanovic, E. Noroozinejad Farsangi, Influence of soil-structure interaction (SSI) on optimal design of passive damping devices. *Structures*, **28**, 847–862, 2020.

[13] R.-J. He and Z.-Y. Yang, Differential evolution with adaptive mutation and parameter control using Lévy probability distribution. *Journal of Computer Science and Technology*, **27**, 1035–1055, 2012.