OPTIMIZATION OF DAMPERS IN VISCOUSLY DAMPED MOMENT FRAMES UTILIZING MOPSO

V. Terzic[(1)], M. Baei[(2)]

[(1)] *Associate Professor, California State University Long Beach, CA, USA, vesna.terzic@csulb.edu*
[(2)] *Formerly Graduate Student, California State University Long Beach, CA, USA, m.baei@yahoo.com*

Abstract

New technological developments in engineering present the opportunity for improved efficiency of structural design through optimization. High-performance computing resources reduce the time needed for computational calculations. Concurrently, optimization algorithms have greatly evolved to provide the opportunity to solve complicated nonlinear engineering problems that typically stipulate conformance to several interrelated, and often conflicting, objectives under a set of constraints.

This study aims to develop the framework for the optimal design of viscously damped moment frames (VDMFs) utilizing the multi-objective particle swarm optimization (MOPSO) algorithm. To allow for seismic applications of nonlinear VDMFs in an efficient way MOPSO is extended to allow for application of constraints on objective functions and utilization of parallel computing. Furthermore, through sensitivity tests, the study provides recommendations on how to generate reliable solution set by proper selection of objective (cost) functions and proper set up of MOPSO input parameters. The proposed strategy is verified utilizing an engineered solution of a viscously damped moment frame. It was found out that under the same set of constraints and performance objectives, MOPSO produces a solution set that contains outcomes that are superior to the engineered solution. For example, the MOPSO solution set contains outcomes that reduce demands on dampers (force and stroke) while maintaining EDPs, generating construction savings as a result of the reduced manufacturing cost of dampers.

Keywords: objective functions; constraint functions; Pareto front; optimal design under constraints; input MOPSO parameters

1. Introduction

Moment frames with supplementary damping devices (i.e., damped moment frames) are often used for the design of new and retrofit of existing buildings as they are known to improve seismic performance at a reasonable cost [1, 2, 3]. The improved performance is achieved by perturbing the energy balance during an earthquake, such that the inelastic dissipation demand on the moment frame is reduced as a result of energy dissipation by the damping devices. Contrary to expectations, a recent study by Terzic et al [4] (which focused on the assessment of seismic performance of different seismic-force resisting systems of commercial low-rise buildings) demonstrated that a damped moment frame designed per minimum ASCE 7-16 requirements achieves inferior performance than a code-compliant special moment frame. This is a direct result of code criteria that permit high interstory drifts (2.5% for low-rise buildings) along with a relatively small strength (0.75% of the seismic base shear based on strength reduction factor (R) of 8), leading to highly flexible and extremely weak system. However, Terzic and Mahin [1] further showed that relatively small investment into larger damping devices stiffens up the frame, yielding significant reductions of repair cost and repair time when compared to a code-compliant special moment frame. Interestingly, the improved (beyond the code) damped moment frame achieves far better performance than a special moment frame at a smaller construction cost. Therefore, in addition to confirming to code requirements, damped moment frames should also confirm to performance objectives set by a client to assure that the desired outcome.

While the current state of design practice mainly relies on manual iterations of design until design and performance objectives are met, modern optimization algorithms supported by high-performance computing (HPC) resources provide an opportunity for solving complex multi-objective non-convex problems in a timely, accurate, and effective manner. Design of a damped moment frame through optimization will not only reduce the time necessary for design but will also reduce the total system cost.

The optimization algorithms have consistently evolved since their conception. Initially, simple single-objective heuristic algorithms, such as the genetic algorithm proposed by Holland in 1975 [5], have progressed into more complicated single-objective metaheuristic algorithms, such as particle swarm optimization (PSO) proposed by Kennedy and Eberhart in 1995 [6]. They have further evolved into multi-objective algorithms supported by the region-based selection methods, such as Pareto Envelope-based Selection Algorithm (PESA) [7,8]. Nowadays, the most prevalent multi-objective evolutionary algorithms are Multi-Objective Genetic Algorithm [9], Non-Dominated Sorting Genetic Algorithm [10], Classic and Intelligent Portfolio Optimization [11], Multi-Objective Evolutionary Algorithm Based on Decomposition [12], and Multi-Objective Particle Swarm Optimization (MOPSO) [13]. Among the multi-objective optimization algorithms, MOPSO has potential to effectively solve engineering problems because it utilizes the small number of starting populations and geographically-based adaptive grids (e.g., PESA [8]) to maintain the diversity of solutions.

Optimization for design or retrofit of systems with dampers has been of interest to engineers and researchers in recent years. In 2014, Castaldo and De Iuliis [14] proposed an integrated optimal seismic design procedure to achieve a design displacement by minimizing a cost index that is a function of elastic and viscoelastic design variables. In 2016, Pollini et al. [15] presented an effective method for minimizing the retrofit costs of viscous dampers by setting a constraint on inter-story drifts. In 2018, Altieri et al. [16] proposed a reliability-based approach that considered the intensity of the seismic inputs to find the optimal solution of the damping coefficients and the velocity exponents for dampers located at different floors of the building while minimizing the sum of the damper forces. Furthermore, in 2018, Wang and Mahin [17] proposed an automated retrofit method with viscous dampers, which utilized single-objective function within the gradient-based optimization algorithm available in OpenSees. While most of the optimization techniques for damped moment frames used in the past are based on a single-objective function and locally optimized solutions, the seismic performance of buildings with dampers mostly depends on several conflicting structural responses (e.g., inter-story drifts and floor accelerations). Therefore, to find an optimal design solution, multi-objective algorithms capable of finding a globally optimal solution set shall be utilized. This study focuses on the optimization of viscous dampers in seismic applications utilizing multi-objective metaheuristic optimization algorithm MOPSO, which finds global minimum while avoiding to get trapped in the local optimal solutions. While Genetic Algorithms can also be used for multi-objective optimization, they are not explored in this study as they typically require a larger population size to find the global minimum than MOPSO, requiring longer computation time.

The study provides an overview of MOPSO and proposes its extension for use in seismic applications of nonlinear systems. This extension includes the application of constraints on objective functions and utilization of parallel computing to improve efficiency and quality of the solution set. Furthermore, through sensitivity tests, the study provides recommendations on how to efficiently generate reliable solution set by proper selection of objective (cost) functions and proper set up of MOPSO input parameters. The proposed strategy is verified utilizing an engineered solution of a viscously damped moment frame.

2. Overview of MOPSO

The original particle swarm optimization (PSO) [6], inspired by the choreography of the flocking of birds, is successfully used for solving single-objective optimization problems. To find an optimal solution, the algorithm performs a multidimensional search, where the behavior of each individual (i.e., particle) is affected by either the best local or the best global individual. The approach allows individuals to benefit from their experience and introduces the use of flying potential solutions through hyperspace to accelerate convergence. Coello Coello and Lechuga [13] have proposed an extension of PSO to allow for multi-objective optimization and named it “multi-objective particle swarm optimization” (MOPSO). Their approach uses the concept of Pareto dominance to determine the flight direction of a particle and establishes a global repository (an external memory) to deposit previously found non-dominated position vectors, which will be used by other particles in the next flying cycle (i.e. iteration) to guide their flight. Additionally, the updates to the repository are performed considering a geographically-based adaptive grids to preserve the diversity of solutions (i.e., diversity of objective function values associated with each particle).

Pareto dominance is a concept implemented in optimization practices to determine whether a certain condition or set of conditions is more desirable in current than in the previous iteration. If the current set of conditions does not worsen any of the outcomes and also improves at least one of the outcomes, then it is said to dominate the previous conditions. This same process leads to the creation of a Pareto front, a set of solutions to an optimization problem where no individual solution is entirely better than any other of the solutions in the set [18]. In MOPSO, nondominated outcomes of each iteration are stored in the repository and are compared to subsequent iterations' outcomes [13]. Because MOPSO is a process meant to optimize several interrelated, and often conflicting, variables, the concept of Pareto dominance is very important.

Although there are many ways to adapt MOPSO [18], the logic of the algorithm typically includes the following elements:

1. *Problem definition:*
    a. Define input (decision) variables.
    b. Define the size of the search space (upper and lower bounds for the input variables).
    c. Define objective (cost) functions; costs must be the function of input variables.
2. *MOPSO input parameters selection*:
    a. Set the number of particles in the swarm (i.e., population size), $nPop$.
    b. Define the repository size (i.e., number of non-dominated particles that can be stored), $nRep$.
    c. Set the maximum number of flying cycles (i.e., number of iterations), $nIter$.
    d. Set parameters that define the criteria for the selection of the new position. These include: inertia weight (w), which keeps particles from traveling too far from one iteration to the next; personal learning coefficient (c_1), which determines how each particle's velocity will be affected by its position; and global learning coefficient (c_2), which determines how each particle's velocity will be affected by the position of the leader.
3. *Problem initialization:*
    a. Initialize the population by arranging the particles randomly within a search space. The particle i is defined with a position vector $x_i = (x_{i1}, x_{i2}, \dots, x_{iD})$, where the dimension, D, of the position vector represents the total number of input variables (i.e., decision variables).
    b. Initialize the speed of each particle by setting them to zero, $v_i = (v_{i1}, v_{i2}, \dots, v_{iD}) = 0$.
    c. Evaluate the costs (objective function values) for each of the particles in the swarm.
    d. Initialize repository and store the positions of particles that represent nondominated vector solutions in the repository.
    e. Generate hypercubes (or grids) of the search space and locate particles using these hypercubes as a coordinate system where each particle's coordinates are defined based on their costs (objective function values).
    f. For each particle initialize the best personal position, $Pbest_i$, by assigning the current position, x_i, to it (i.e., $Pbest_i = x_i$). This info will be stored in the repository and used to guide the travel of particles through the search space.
4. *MOPSO main loop:* For each iteration (i.e., flying cycle) and each particle in the swarm do the following:

a. Use roulette wheel selection to select the leader among nondominated particles. The position of the leader is designated as the global best position, $Gbest$.

b. For iteration n, compute the speed of a particle i for an input variable j (where j goes from 1 through D) using Equation 1:

$$v_{ij}^{n} = w \cdot v_{ij}^{n-1} + c_1 \cdot r_{1,ij}^{n} \cdot \left(Pbest_{ij}^{n-1} - x_{ij}^{n-1}\right) + c_2 \cdot r_{2,ij}^{n} \cdot \left(Gbest_{j}^{n-1} - x_{ij}^{n-1}\right) \tag{1}$$

where $r_{1,ij}^{n}$ & $r_{2,ij}^{n}$ are random numbers uniformly distributed between 0 and 1.

c. Compute the new positions of the particles by adding new speed to the position of the last cycle using Equation 2:

$$x_{ij}^{n} = x_{ij}^{n-1} + v_{ij}^{n} \tag{2}$$

d. Maintain particles in the search space in case they go beyond the boundaries.

e. Evaluate objective functions for each of the particles in the swarm.

f. Update the contents of repository (positions of nondominated particles) together with the geographical representation of the particles within the hypercubes (or grids).

g. Use Pareto dominance to decide whether the current position of the particle is better than the personal best from the previous cycle. If the personal best position from the previous cycle is dominated by the new position, the personal best position is updated using Equation 3, and stored in the repository. Otherwise, the repository keeps the old value.

$$Pbest_{ij}^{n} = x_{ij}^{n} \tag{3}$$

Note that the relationship structure between particles (i.e., neighborhood topology) presented here is one of many possible topologies that can be used within MOPSO. Other possible adoptions include but are not limited to: specifying bounds for the velocity of a particle; establishing constraints for objective functions; use of constriction coefficients [19] to calculate the search parameters. Given its flexibility and robustness, MOPSO can be expanded to allow for tackling new types of optimization problems.

3. Adoption of MOPSO for use with Viscously Damped Moment Frames

The focal point of the paper is the evaluation and adoption of MOPSO algorithm for use in finding optimal design solution set of viscously damped moment frames. A three-story building with viscously damped moment frames (VDMFs) located at the building perimeter was utilized in support of this study. Moment frames of a VDMFs confirm to the strength requirement of ASCE 7-16; they were designed for 0.75% of the seismic base shear, which was based on the strength reduction factor (R) of 8. In this optimization problem, damping coefficients of dampers are selected to be the only input variables to provide an initial insight into the usability of MOPSO in seismic applications (see Section 3.1 for more details). The other damper's properties, stiffness and velocity exponent, are adopted from the engineered design solution [1] and take values of 2000 kips/in. and 0.5, respectively. The main task of this optimization problem is a selection of damper properties that will yield benefits in terms of seismic performance and/or construction cost. The main objective functions include dampers' forces and global structural responses that are directly tied to performance: interstory drifts, floor accelerations, and residual drifts (typically referred to as engineering demand parameters, EDPs).

As a starting point, the study utilizes Yarpiz's adoption of MOPSO [20], with its implementation in MATLAB. This adoption incorporates Pareto Envelope and the grid making technique to find non-dominated solutions and to select the leader. New input parameters include: density of the search space ($nGrid$), which affects selection of the leader; inflation rate (α), which helps expend the search space; leader selection pressure (β), which helps roulette wheel selection of the leader; deletion selection pressure (γ), which helps roulette wheel selection of particles to be deleted from repository; and mutation rate (μ), which slightly alters position to push particles further towards an optimized solution.

For this study, Yarpiz's adoption is expended by introducing constraints of objective functions and by allowing for parallel computing. In our adoption of MOPSO, objective functions (e.g., interstory drifts, floor accelerations, residual drifts, dampers' forces) are evaluated for randomly selected values of input variables (i.e., damping coefficient of dampers at different stories) utilizing the nonlinear structural model of VDMF created in computational software OpenSees [21]. MATLAB was used as an interface to facilitate interaction between OpenSees and MOPSO. To be computationally efficient, simulations are performed utilizing parallel computing options in MATLAB, allowing for simultaneous cost evaluations for all particles in one flaying cycle (iteration). Codes that facilitate our adaptation of MOPSO are publicly available [22].

This section of the paper explores the sensitivity of the solution set to: (1) definition of objective (cost) functions and (2) choice of influential MOPSO input parameters isolated by Thomas [23]: density of the search space, population size, and the number of iterations. All other MOPSO input parameters are adopted from a study by Thomas [23], where the recommendation is derived from a sensitivity study that explores the effect of all MOPSO input parameters for the case of an elastic single-degree-of-freedom (SDOF) system subjected to an earthquake. These MOPSO parameters are maintained constant in this study with the following values: w=0.05, c_1=1.9, c_2=1.9, α=0.01, β=1.0, γ=3.0, μ=0.1 (definition of parameters are provided in Sections 2 and 3).

To provide content to the study, the sensitivity tests are conducted considering a strong ground motion representative of an earthquake with 2% probability of exceedance in 50 years under the following constraints: "maximum" interstory drift (mISD) limit of 2%, "maximum" floor acceleration (mFA) limit of 0.85g, and "maximum" residual interstory drift (mRISD) limit of 0.5%. Within the context of this study, the "maximum" response represents the maximum of peak responses across all building floors/stories attained during an earthquake. Similarly, the "average" response will refer to the average of the peak responses. It is to be noted that constraints typically limit the solution set by improving their quality. However, stiff constraints may increase the runtime because, if any of the constraints is not satisfied, the particle failed to meet a constraint is substituted with another particle and evaluation of objective functions is repeated.

3.1 VDMF configuration and selected ground motion

VDMFs of a three-story steel office building had six bays with a spacing of 30ft, a typical story height of 15ft, and a first story height of 17ft (Fig. 1). The site soil class was D, with shear wave velocity of 180 to 360 m/s. The building was located in Los Angeles at a site characterized by spectral accelerations of S_s=2.2g (for short period) and S_1=0.74g (for a period of 1s). The building was modeled in OpenSees [21] by Terzic and Mahin [1] with viscous dampers modeled utilizing Maxwell model (linear spring and nonlinear dashpot in series). It is to be noted that dampers of VDMF were originally designed by Miyamoto International, Inc. with the design objective to limit the interstory drifts at the design level earthquake to 1%. To meet the imposed requirement, dampers had viscous damping of 135 kip/(in./sec)$^{0.5}$ at first two stories (designated as C12) and 35 kip/(in./sec)$^{0.5}$ at the third story (designated as C3). It is known that damping coefficients of dampers have a significant effect on structural response [1] and are therefore selected as input (decision) variables in this optimization study. The search space is defined as follows: C12 range is set to 120-160 kip/(in./sec)$^{0.5}$ and the C3 range is set to 20-60 kip/(in./sec)$^{0.5}$. Note that the selected ranges of damping coefficients encompass design solutions.

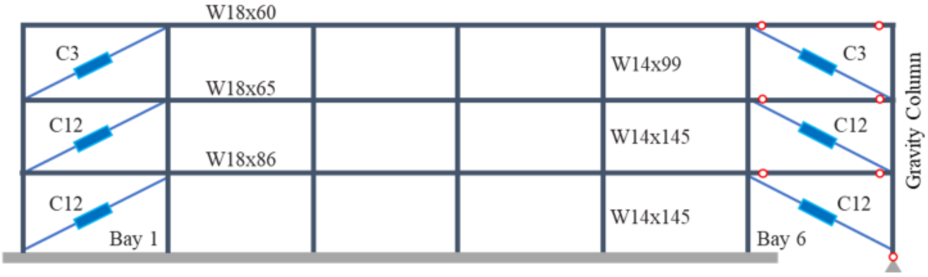

Fig. 1 - Configuration of VDMF.

The ground motion utilized for the sensitivity study is El Centro ground motion (NGA record number 6 within PEER ground motion database), scaled 3.63 times to represent very high seismic hazard for the considered site; it is representative of an earthquake with 2% probability of exceedance in 50 years. The acceleration time history of the scaled ground motion is displayed in Fig. 2.

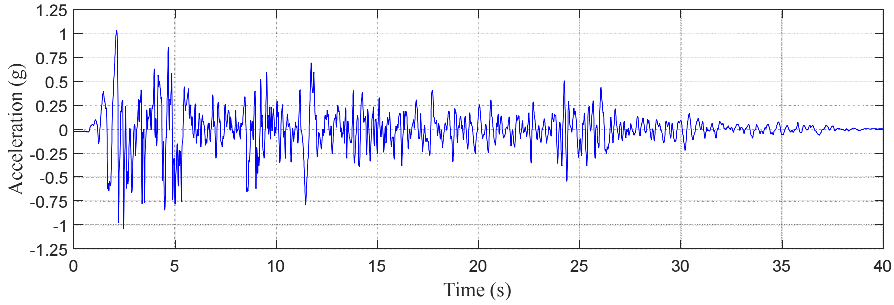

Fig. 2 – Acceleration time history of the selected ground motion (scaled).

3.2 Effect of a selected set of cost functions on the diversity of the solution set

This section explores the effect of the selected cost (objective) functions on the quality of the solution set. In this sensitivity test, the major MOPSO input parameters are maintained constant with the following values: $nPop$=30, $nGrid$=7, $nIter$=5. Initially, a total of nine different sets of cost functions are explored and presented by Baei [22]. This paper focuses on the results of three sets of cost functions that provide the most insight. These cost functions include consideration of only global structural responses (e.g., drifts, accelerations, residual drifts) as well as consideration of a combination of global structural responses and dampers' forces (evaluated indirectly by considering damping coefficients). In particular, Fig. 3 compares decision variable outcomes under the selected set of constraints for the following cost function sets: (1) [mISD, mFA, mRISD] (left figure), (2) [mISD, mFA, mRISD, C12, C3] (middle figure), and (3) [mISD, mFA, mRISD, C12, C3, C12+C3] (right figure). Runtimes for the three sets of cost functions were similar and ranged from 4.06 hours (for set 1) to 4.52 hours (for set 3).

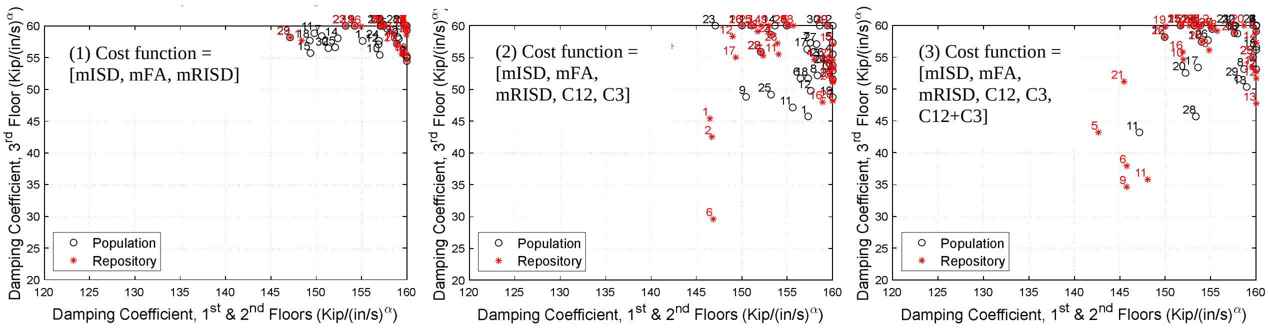

Fig. 3 - Effect of selected cost functions on the decision variable sets ($nPop$=30, $nGrid$=7, $nIter$=5).

The results presented in Fig. 3 show that cost functions that only consider global structural responses (left figure) provide a set of decision variables (repositories of MOPSO) that are concentrated at the upper-right corner of the search space (higher end of the range of damping coefficients). Attained solutions may yield non-optimal design of dampers as there are possible deviant values with relation to other cost functions not considered in this initial cost function set. This was a motivation for exploring additional cost function sets. It was found out that consideration of dampers' forces (i.e., damping coefficients) as cost functions in addition to the global structural responses (shown in the middle figure) diversifies the solution set. Furthermore, adding a linear combination of dampers' forces to the previous set of cost functions (shown in the right figure) provides additional benefit. This final cost function set, (3), is therefore selected for further use in sensitivity studies that follow. Presented results also exemplify that cost functions typically used by the research community, which include only drift, only damping coefficients, or combination of drift and acceleration, would not generate optimized solutions utilizing MOPSO. Finally, it is to be noted that while significant improvement in the diversity of the solution outcomes is achieved through the selection of the cost function, there is a potential for further improvements by altering the major MOPSO parameters.

3.3 Effect of MOPSO input parameters on the diversity of the solution set

Previously, Thomas [23] investigated the effect of different MOPSO input parameters on the quality of solution outcomes of an SDOF system subjected to an earthquake. It was reported that population size, the density of the search space, and the number of iterations had a particularly significant impact on solutions. Therefore, these MOPSO parameters will be altered to highlight their effect on solution outcomes in the case of nonlinear structural behavior. Cost function set (3), introduced in Section 3.2, will be used in support of this sensitivity study. It is to be noted that in this adoption of the MOPSO number of iterations is the only MOPSO parameter that has a significant effect on computation time.

The effect of density of the search space, $nGrid$, on the decision variable outcomes is explored by considering the following values of $nGrid$: 7, 10, and 15. In this sensitivity test, population size ($nPop$) was set to 30 and the total number of iterations ($nIter$) was set to 5. The results presented in Fig. 4 demonstrate the great impact of $nGrid$ parameter on the results of optimization. It is apparent that higher values of $nGrid$ generate more diverse decision variable outcomes. In this particular study, $nGrid$ of 15 provides sufficient diversity and is therefore selected as a benchmark value for all further sensitivity tests.

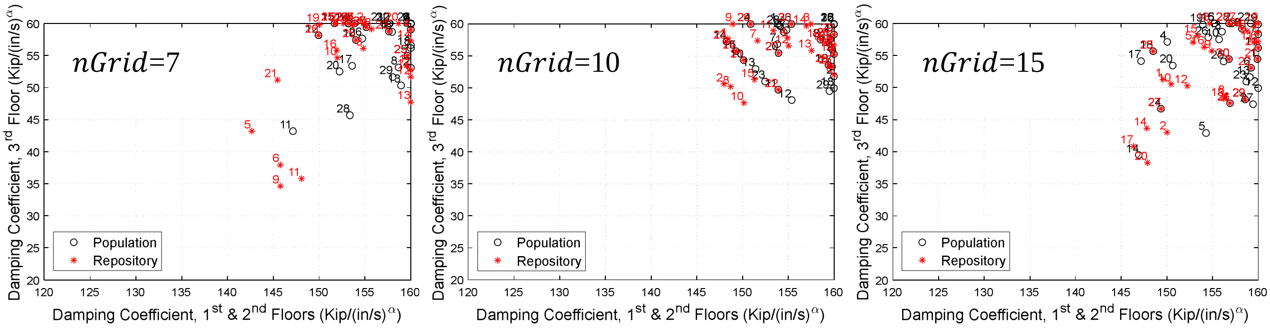

Fig. 4 - Effect of density of search space, $nGrid$, on the decision variable outcomes ($nPop$=30, $nIter$=5).

The effect of population (swarm) size, $nPop$, on the decision variable outcomes is next explored by considering the following values of $nPop$: 10, 20, and 30. In this sensitivity test, the density of the search space ($nGrid$) was set to 15 and the total number of iterations ($nIter$) was set to 5. The results presented in Fig. 5 show that decision variable outcomes dramatically improve with the increase in population size from 10 to 30. These results accentuate the importance of population size on the optimization results. In this study, $nPop$ of 30 generated sufficient diversity of decision variable outcomes and is used as a benchmark value for all subsequent tests. Finally, it is important to note that if HPC resources that support parallel computing are available, an increase in population size should not have an impact on the MOPSO runtime.

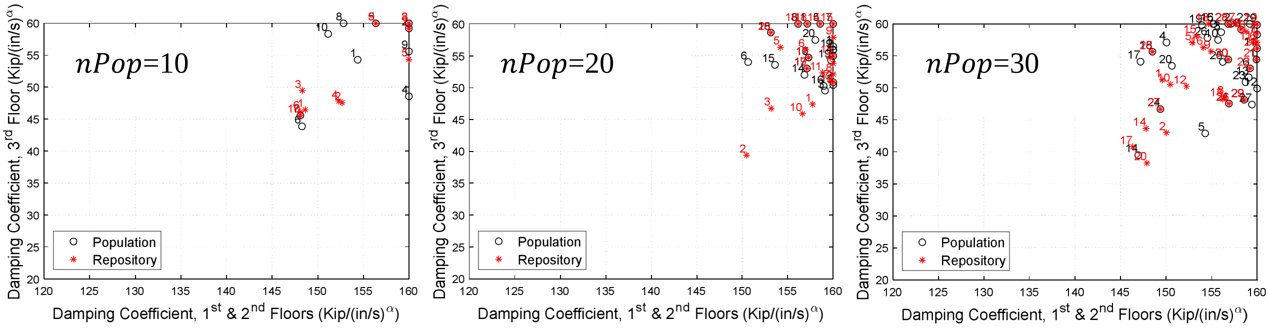

Fig. 5 - Effect of the number of particles in population, $nPop$, on the decision variable outcomes ($nGrid$=15, $nIter$=5).

The last MOPSO parameter explored herein is the number of iterations (i.e., flying cycles), $nIter$. It is altered to take the following values: 1, 3, and 5. This test uses knowledge from the two prior tests; therefore $nGrid$ is set to 15 and $nPop$ is set to 30. Fig. 6 shows that each explored case provides a diverse decision variable outcome. However, as the cost functions get optimized with each iteration, the results show the migration of non-dominated particles in repositories towards the upper-right corner of the search space. In this study, 5 iterations achieved satisfactory MOPSO solutions and are used in the subsequent sections of this paper.

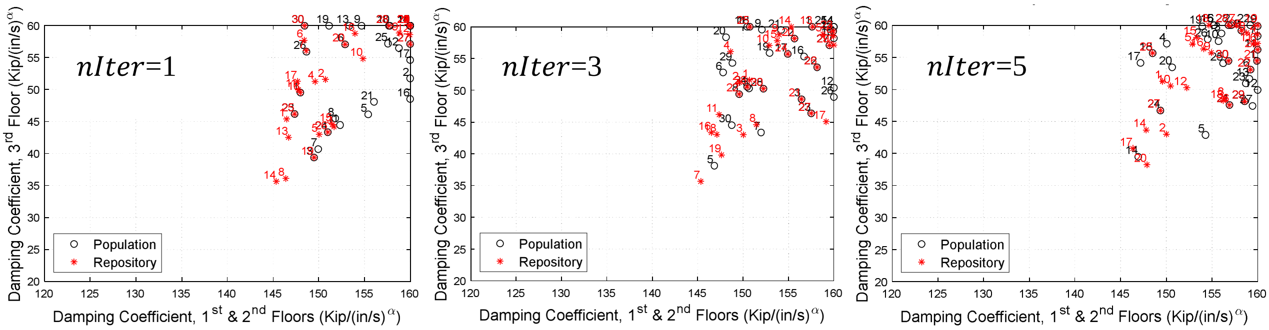

Fig. 6 - MOPSO decision variable outcomes for different number of considered iterations, $nIter$ ($nPop$=30, $nGrid$=15)

3.4 Comparison of solution outcomes when "maximum" or "average" of an EDP is used as a cost function

Building on the results of sensitivity studies presented in Sections 3.2 and 3.3, this section shows the effect of the choice of response measure ("maximum" or "average") in the cost function on the MOPSO solution set. Meanings of "maximum" and "average" responses are next explained with an example. For instance, "maximum" ISD is the maximum of peak ISDs from all stories, where peak ISD of one story represents maximum ISD (in the absolute sense) attained at that story during the considered earthquake. Similarly, "average" ISD is the average of peak ISDs.

Fig. 7 shows decision variable outcomes across the search space for the two considered choices of response measure in the cost function, "maximum" (left figure) and "average" (right figure). In both cases, the decision variable outcomes fall within the same area of the search space following a similar pattern; however, the outcomes associated with "maximum" response measures are less dense. Furthermore, Fig. 8 compares Pareto fronts of FAs and ISDs for the two choices of response measures by illustrating "minimum", "average", and "maximum" response for each particle in the repository. Both of the choices result in the same pattern of Pareto fronts, where the choice of the "maximum" response measure in cost function generates a wider range of solutions as a result of a higher diversity of decision variable outcomes.

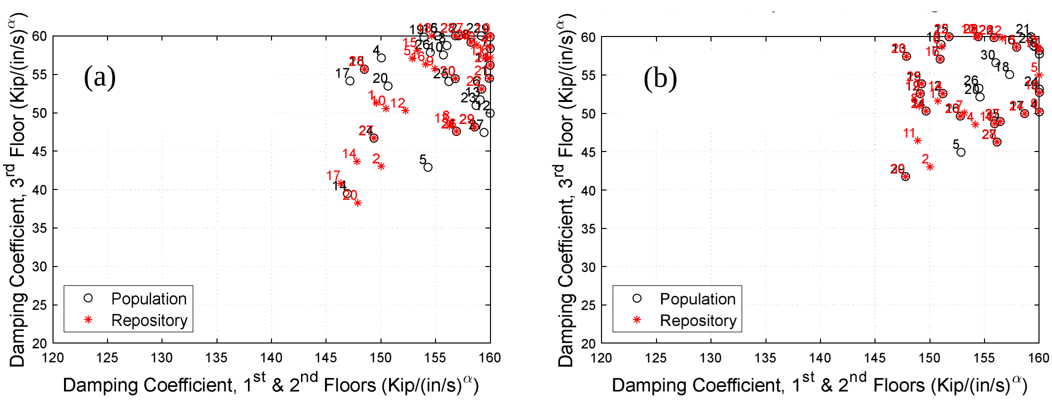

Fig. 7 - MOPSO decision variable outcomes when: (a) "maximum" of an EDP is used as the cost function, (b) "average" of an EDP is used as the cost function.

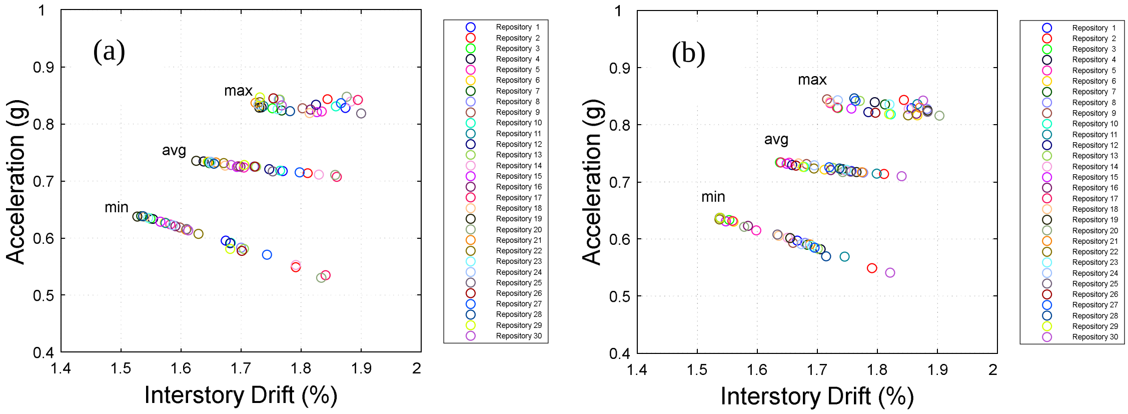

Fig. 8 – Pareto fronts of minima, averages, and maxima of peak responses (i.e., floor accelerations and interstory drifts) across all building floors/stories for the cases where: (a) "maximum" of an EDP is used in cost function, (b) "average" of an EDP is used in cost function.

The sensitivity study presented in this section provides recommendations on how to implement MOPSO for the design optimization of a VDMF. It demonstrates the importance of the proper selection of cost functions, the density of the search space, population size, and the number of iterations. It further shows that in the case of a 3-story building, the MOPSO solution set is insensitive to the choice of "maximum" or "average" EDP in the cost function. While this paper presents MOPSO results where decision variable ranges are somewhat narrow, Baei [22] shows that MOPSO provides an equally good solution set for much wider ranges of decision variables. However, it is noted that required computation time increases with the increase of the search space.

4. Verification of the proposed MOPSO framework for VDMF

The main goal of this section is the verification of the proposed MOPSO adaption for the optimal design of VDMFs. This is achieved by comparing the MOPSO solution set with the engineered design solution (as described in Section 3.1). Both, MOPSO and an engineered solution are derived for the set of three spectrally matched ground motions. The pseudo-acceleration response spectra of the considered ground motions along with the designed spectrum are shown in Fig. 9. Response history analysis of engineered VDMF subjected to three selected ground motions generated the maximum interstory drift of 0.99%, maximum floor acceleration of 0.48g, and maximum residual interstory drift of 0.018%. To assure optimal design solution with MOPSO, the following constraints were utilized: 1.2% for interstory drifts, 0.5g for floor accelerations, and 0.2% for residual interstory drifts.

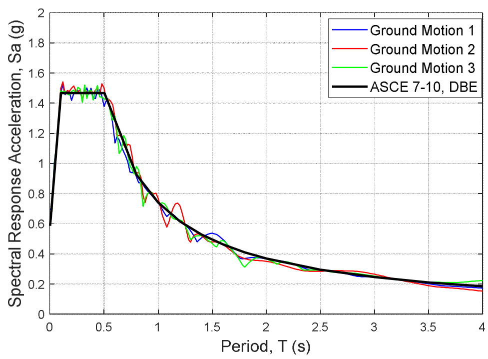

Fig. 9 - The design spectra, and ground motions selected for designed VDMF.

The MOPSO parameters utilized for finding the set of optimal solutions stem from sensitivity studies presented in Section 3 and take the following values: $nPop$=30, $nGrid$=15, $nIter$=5. Given that the manufacturing cost of a damper depends on its force and stroke capacity, the objective functions recommended in Section 3 are altered to replace ISD with the damper's stroke, and damping coefficients with the dampers' forces. This alteration shall not affect the quality of the MOPSO solution set [22]. Therefore, objective functions used in this verification study include "maximum" values of the following structural responses: dampers' stroke, FA, RISD, damper force for dampers of the first two stories (F12), damper force for dampers of the third story (F3), and linear combination of dampers' forces (F12+F3). Decision variables are still damping coefficients C12 and C3, but in this case, the search space is set assuming that prior engineering knowledge is not available. The same range (0-300 kip/(in./sec)$^{0.5}$) is assigned to both C12 and C3.

Fig. 10(a) shows Pareto front in terms of "maximum" damper stroke and "maximum" floor acceleration. Under the given set of constraints, floor accelerations almost linearly decrease with the increase of the stroke. To accommodate the constraints (1.2% on interstory drifts and 0.5g on floor accelerations), maximum stroke ranges from 1.45 in. to 2.1 in. while maximum floor acceleration ranges from 0.42g to 0.49g. Furthermore, Fig 10(b) shows that the maximum force of dampers located on the first two stories is generally greater than that of the third story. This implies larger damping coefficients for the bottom two stories than at the 3rd story.

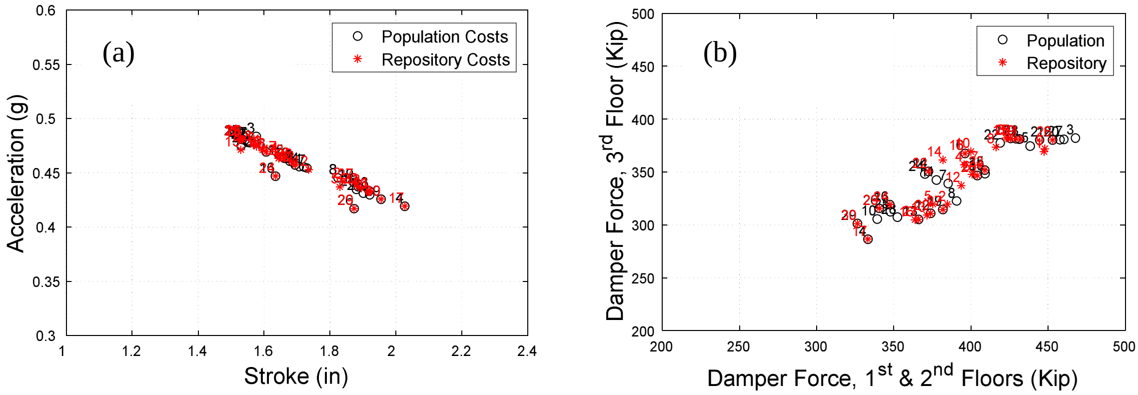

Fig. 10 – (a) Pareto front ("maximum" damper stroke vs. "maximum" floor acceleration) and (b) dampers' forces.

The profiles of maximum forces and strokes of dampers are shown in Fig. 11 for all particles in the repository, along with the profiles of the engineered solution (black dashed line). By investigating MOPSO solutions, it was found out that particle #3 (black solid line in Fig. 11), generates slightly smaller ISDs, FAs, and RISDs (up to 3%) than the engineered solution while producing smaller demands on dampers; it has about 20% smaller damper force demand and about 10% smaller stroke demand. Damping coefficients associated with particle #3 are 134.5 kip/(in./sec)$^{0.5}$ and 42.39 kip/(in./sec)$^{0.5}$ for C12 and C3, respectively. While C12 is approximately the same as the engineered solution (135 kip/(in./sec)$^{0.5}$), C3 is 20% higher than the engineered solution (35 kip/(in./sec)$^{0.5}$). To conclude, it is to be stressed out that achieved reduction in damper demands, while maintaining EDP responses, translates in construction savings as a result of reduced manufacturing cost of dampers. Furthermore, particle #8 (red solid line in Fig. 11) with C12 of 131 kip/(in./sec)$^{0.5}$ and C3 of 43 kip/(in./sec)$^{0.5}$, produces similar demands on dampers as the engineered solution, while reducing "maximum" ISDs by 15%. This implies better seismic performance at the same construction cost. These examples demonstrate the power and efficiency of MOPSO in seismic applications.

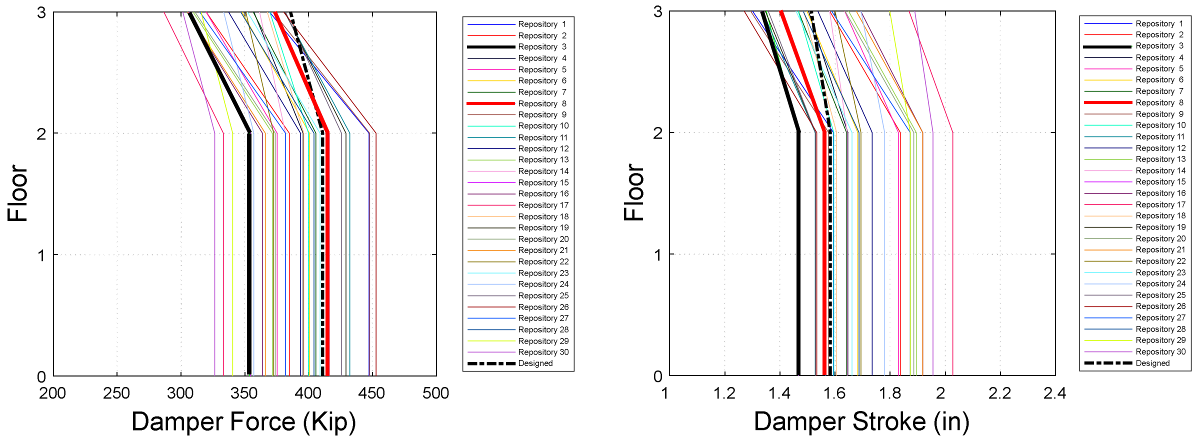

Fig. 11 - Dampers' forces and strokes for MOPSO (original VDMF design, black dashed line; repository 2, tick red line).

5. Summary and Conclusions

This study focuses on the optimization of viscous dampers for seismic applications utilizing multi-objective particle swarm optimization (MOPSO) algorithm. MOPSO with its inherent metaheuristic approach and geographically-based adaptive grids avoids getting trapped in the local optimal solutions and effectively discovers diverse non-convex solutions. To further improve the efficiency of the search considering an engineering application, MOPSO is expended by applying constraints on objective functions and by allowing for parallel computing.

The study provides recommendations on how to adequately use MOPSO to generate reliable solution set is seismic applications. Special emphasis is placed on the definition of objective functions, set up of MOPSO input parameters, and parallel computing utilizing high-performance computing resources. The presented study reveals that cost functions that only contain EDPs generate locally optimized solutions, while consideration of EDPs along with dampers' forces improves the solution set. Furthermore, the study highlights the importance of proper set up of MOPSO parameters (density of the search space, population size, and the number of iterations) and demonstrates their effect on the solution outcomes through sensitivity studies. The proposed MOPSO adoption for design of VDMF is verified through a comparison of the MOPSO solution set with an engineered design solution. It was found out that the MOPSO solution set contains outcomes that reduce damper demands (force and stroke) by 10-20% relative to the engineered solution, while maintaining EDP responses similar. This translates into construction savings as a result of reduced manufacturing cost of dampers. Additionally, MOPSO solution set contains the outcomes that reduce "maximum" ISDs by 15%, while generating similar demands on dampers as the engineered solution. This implies better seismic performance at the same construction cost, demonstrating the power and efficiency of MOPSO in seismic applications.

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