

Comparative Study on Optimal Distribution of Viscous Dampers Using Genetic Algorithm and Intelligent Water Drops Under Energy-Compatible Endurance Time Excitations

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ABSTRACT

Nonlinear time-history analysis (NLTHA) remains one of the most rigorous tools for evaluating the seismic performance of structures; however, its high computational cost limits practical application within optimization frameworks. The endurance time (ET) method, which applies intensifying accelerograms to structures, enables continuous assessment of seismic demands across multiple hazard levels with a significantly reduced number of analyses. This study investigates the optimal distribution of fluid viscous dampers (FVDs) in a three-story deficient steel moment-resisting frame using the ET method, subject to performance-level constraints prescribed by ASCE/SEI 41-06 at the life safety (LS) and collapse prevention (CP) levels. Two metaheuristic algorithms – a standard genetic algorithm (GA) and the intelligent water drops (IWD) algorithm – are employed in a controlled comparative setting with identical modeling assumptions, objective functions, and constraint formulations. The optimization problem is formulated to minimize the total damping demand while satisfying interstory drift ratio (IDR) limits at basic safety earthquake (BSE) hazard levels BSE-1 and BSE-2. The study further extends the formulation to a multi-objective framework that simultaneously addresses peak drift, peak floor acceleration, and total damper cost. Results demonstrate that both algorithms concentrate the dominant damping contribution at the second story, consistent with the fundamental mode deformation profile. The IWD algorithm exhibits faster convergence and achieves a marginally lower total damping coefficient (approximately 6-9% reduction in mean IDR) compared with GA, while both algorithms satisfy the prescribed performance limits. Validation against conventional NLTHA confirms that ET-based predictions remain within an acceptable engineering error margin of less than 12%. Energy balance analyses indicate that FVDs dissipate approximately 35-45% of seismic input energy, confirming the efficacy of the supplemental damping system.

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1. Introduction

Passive energy dissipation systems have emerged as one of the most effective strategies for mitigating seismic demands on building structures and improving their overall seismic performance [1-3]. Among the various supplemental damping devices available, fluid viscous dampers (FVDs) have gained widespread adoption in earthquake engineering practice owing to their high energy dissipation capacity, velocity-dependent force-displacement behavior, and stable hysteretic performance under severe

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ground motions [1]. The out-of-phase relationship between peak damper force and peak structural displacement makes FVDs particularly attractive, as supplemental damping can be introduced without a commensurate increase in structural base shear.

In performance-based seismic design (PBSD), structures are required to satisfy multiple performance objectives at distinct hazard levels, necessitating nonlinear time-history analyses (NLTHA) under ensembles of appropriately scaled ground motion records [4, 5]. The computational burden of repeated NLTHA within an iterative optimization loop renders direct performance-based optimization challenging, particularly for parametric studies involving large variable spaces. The endurance time (ET) method, originally proposed by E.Estekanchi et al. [6, 7] and Riahi and Estekanchi [8], addresses this limitation by subjecting structures to a set of pre-designed, intensifying acceleration functions – termed endurance time excitation functions (ETEFs) – that produce monotonically increasing spectral demands over time. By mapping analysis time to hazard intensity through spectral compatibility, the ET method enables continuous evaluation of structural response across a spectrum of seismic intensities from a single dynamic analysis, thereby reducing computational cost by an order of magnitude relative to conventional multi-record NLTHA.

The optimization of supplemental damping distribution has been extensively investigated using a variety of heuristic and metaheuristic algorithms. Genetic algorithms (GAs), first formalized by Holland [9] and subsequently popularized by Goldberg [10], remain the most widely employed evolutionary technique for structural optimization problems. More recently, swarm-intelligence algorithms have attracted attention owing to their favorable exploration-exploitation balance. The Intelligent Water Drops (IWD) algorithm, introduced by Shah-Hosseini [11, 12], is a population-based metaheuristic inspired by the natural dynamics of water flow in river systems, where soil erosion and sediment transport govern path selection. Despite its successful application to combinatorial and continuous optimization problems [13], IWD has received limited attention in the context of performance-based seismic design of structures equipped with supplemental dampers.

Several recent studies have addressed related aspects of supplemental damper optimization. Shirkhani et al. [14] employed the ET method with GA to optimize FVD distributions in steel frames using hysteretic-energy-compatible excitations. Pollini [15] proposed a fail-safe optimization framework for viscous dampers considering device malfunction scenarios. Bakhshinezhad and Mohebbi [16] utilized NSGA-II for multi-objective design of semi-active FVDs in nonlinear structures. Aydin et al. [17] developed optimal damper distribution strategies for planar building rehabilitation. Mohsenian et al. [18] applied the ET method to estimate multi-level response modification factors for steel moment frames. Ayyash and Hejazi [19] proposed a hybrid PSO-GSA algorithm for performance-based optimization of structures with vibration dampers. Artar and Carbas [20] investigated optimal sizing of steel frames equipped with friction dampers using the grey wolf optimizer. Patsialis et al. [21] addressed the optimal design of tuned-mass-damper-inerter systems for hysteretic multi-story buildings. Lara-Valencia et al. [22] applied a whale optimization algorithm for TMD design, while Farzam et al. [23] reviewed various approaches for optimal structural control. Mazza et al. [24] examined the seismic vulnerability of base-isolated hospital structures using advanced bearing models.

Despite these advances, few studies have conducted a controlled, like-for-like comparison of different metaheuristic algorithms within a unified ET-based performance-based optimization framework. The novelty of the present study resides not merely in comparing two algorithms but in establishing a rigorous comparative platform where the structural model, ETEF set, objective function, constraint formulation, and verification procedure are held constant, thereby isolating the net effect of the optimization algorithm on the final design. Specifically, the contributions of this paper are threefold:

- (I) an ET-based, performance-constrained optimization framework is implemented for FVD distribution under ASCE/SEI 41-06 [5] acceptance criteria;
- (II) the IWD algorithm is introduced as a competitive alternative to GA for this class of problems and benchmarked under identical conditions;
- (III) the results are extended to a multi-objective formulation, supported by parametric sensitivity analysis, independent ET validation against NLTHA, and energy-balance assessment.

To further clarify the novelty of this work, the present study makes the following distinct contributions beyond existing literature:

- (a) it is the first to apply the IWD algorithm to the performance-based optimization of supplemental damping systems, thereby introducing a new computational tool to this domain;
- (b) the controlled comparison eliminates confounding variables that typically hinder fair algorithm benchmarking in structural optimization studies, as the structural model, analysis method, objective function, and constraint handling are held strictly identical;
- (c) the integration of hysteretic-energy-compatible ETEFs with metaheuristic optimization enables a computationally efficient yet physically meaningful performance assessment that accounts for cumulative damage;
- (d) the multi-objective extension and parametric sensitivity analysis provide design guidance beyond the single optimal solution, offering practitioners a range of non-dominated alternatives.

Fig. 1 illustrates the three-story, single-bay steel moment-resisting frame adopted as the benchmark structure, including the member cross-sections, story dimensions, and the locations of the viscous dampers. The dampers are installed in diagonal configurations at each story, allowing the story-level damping coefficients (c_1), (c_2), and (c_3) to be independently optimized. The configuration shown in Fig. 1 therefore defines the structural and design-variable framework used throughout the optimization procedure.

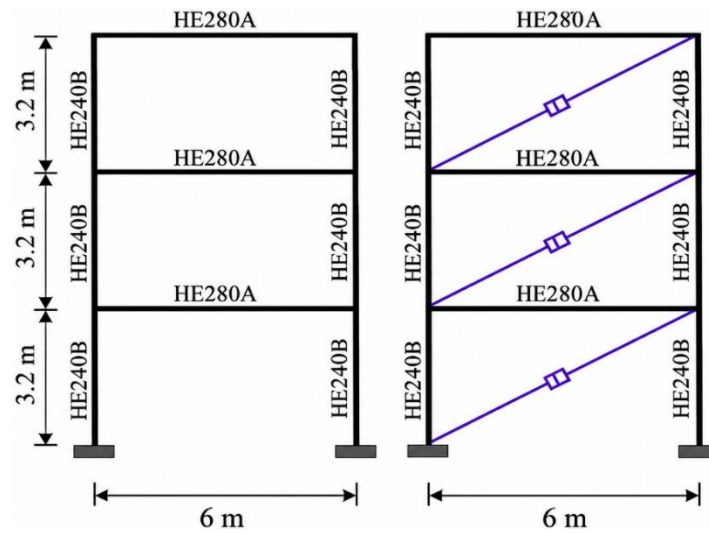


Fig. 1. General configuration of the three-story steel moment-resisting frame with member cross-sections and damper placement adapted from Shirkhani et al. [14].

2. Endurance time method

In the ET method, the structure is subjected to a pre-designed intensifying excitation function (ETEF) and its response quantities are recorded as continuous functions of time. Analysis time is mapped to seismic hazard intensity through spectral compatibility at selected periods, allowing direct comparison of structural response with code-specified performance limits at any desired hazard level without additional analyses [6, 7]. In the present work, hysteretic-energy-compatible ETEFs from the ETA20kd series are employed. The equivalent ET times for the structure under consideration are 15.4 s for BSE-1 and 19.9 s for BSE-2, corresponding to scale factors of 1.31 and 1.82, respectively (Table 1). Fig. 2 illustrates the overall workflow adopted in the present study, including the ET-based seismic evaluation, generation of candidate damper distributions, optimization process, and final verification through conventional nonlinear time-history analysis. The workflow highlights the integration of the ET method with the IWD and GA optimization algorithms and shows how the performance constraints are incorporated into the optimization procedure.

Table 1. Equivalent ET times and corresponding scale factors for the study structure.

Hazard level	ET time (s)	Scale factor
BSE-1	15.4	1.31
BSE-2	19.9	1.82

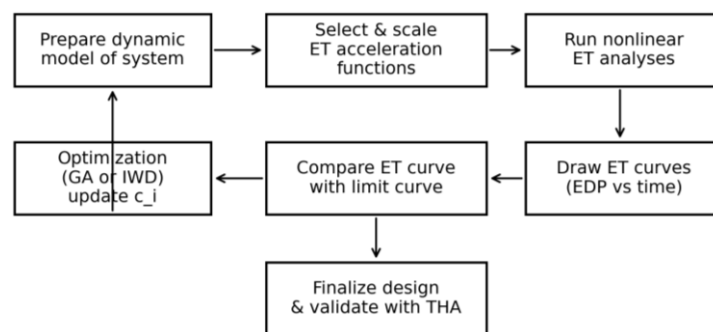


Fig. 2. General methodology for utilizing the ET method in optimal design procedure.

The ETA20kd series used in this study was developed by Mashayekhi et al. [25] through an optimization process that ensures compatibility with both acceleration response spectra and hysteretic energy spectra at multiple time targets. The intensifying nature of ETEFs provides a key advantage: a single analysis encodes the structural response at all intensity levels, enabling multi-level performance assessment without repeated analyses. The theoretical basis of ETEF generation is discussed in detail by Estekanchi et al. [26], who formulated the excitation functions as constrained optimization problems targeting spectral compatibility at discrete time windows.

Fig. 3 presents the target acceleration spectrum together with the normalized spectra used for the generation and assessment of the endurance time excitation functions. The figure provides the spectral basis for establishing the correspondence between the ET excitation and the target seismic hazard levels. Fig. 4 further illustrates the spectral compatibility between the ETEF response spectra and the corresponding target spectra at selected analysis times. The close agreement at the considered time instants confirms that the adopted ETA20kd excitation functions provide the required progressive representation of seismic intensity for the subsequent ET-based analyses. Fig. 5 shows an example of the intensifying excitation function used in the ET analysis. As the analysis time increases, the amplitude of the excitation progressively increases, allowing different levels of seismic intensity to be represented within a single dynamic analysis. This characteristic is fundamental to the computational efficiency of the ET-based optimization framework adopted in this study.

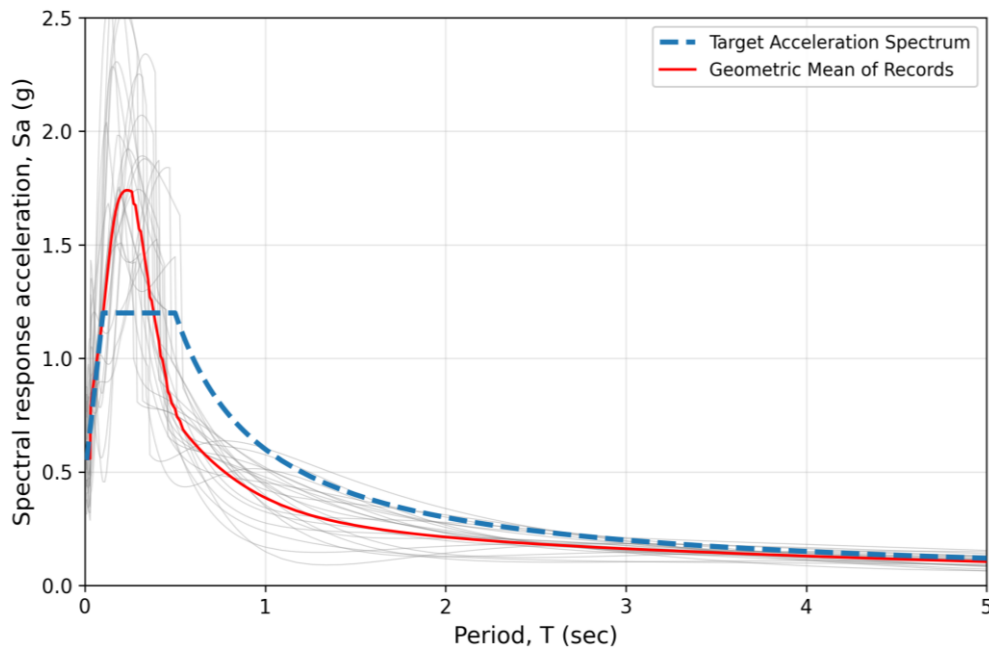


Fig. 3. Target acceleration spectrum and normalized far-field spectra used for ETEF simulation.

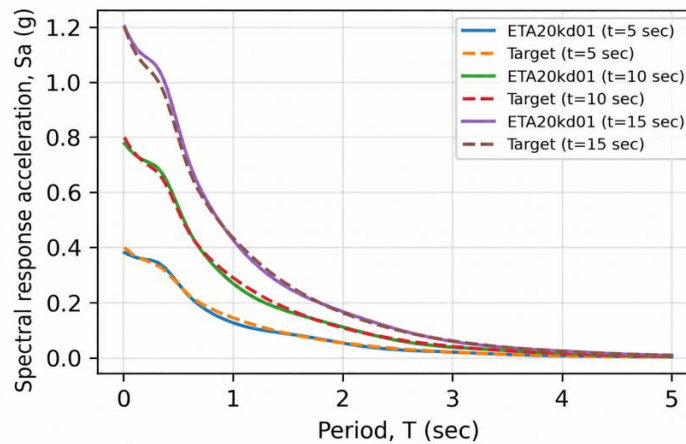


Fig. 4. Compatibility between ETEF response spectra and target spectra at $t = 5, 10$, and 15 s.

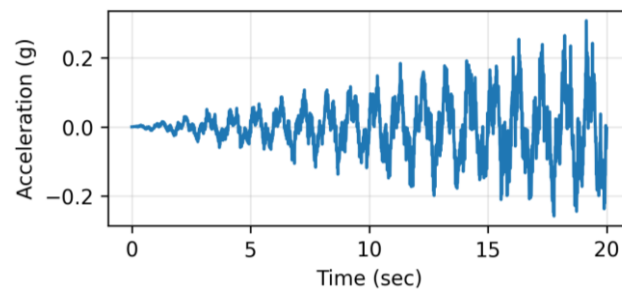


Fig. 5. Example intensifying excitation function (synthetic ETA20kd01-like record).

The ET-based optimization workflow proceeds as follows: (a) the deficient bare frame is analyzed under the ETEF set to identify performance deficiencies; (b) candidate damper distributions are generated by the optimization algorithm; (c) each candidate is evaluated via ET analysis to extract peak IDR at the target ET times; (d) constraint satisfaction is checked against ASCE/SEI 41-06 [5] drift limits; and (e) the process iterates until convergence. The final optimized design is subsequently verified through conventional NLTHA under a suite of recorded ground motions to confirm consistency between ET-based screening and detailed time-history assessment.

3. Structural model and damper configuration

3.1. Steel frame model

A three-story, single-bay steel moment-resisting frame with an identified design deficiency is adopted as the benchmark structure, following the model originally developed by Estekanchi et al. [6, 7] and subsequently employed by Shirkhani et al. [14]. The frame was designed for one-half of the base shear recommended by the Iranian Standard 2800 [27] for a region of high seismicity, resulting in a structure that fails to satisfy the drift acceptance criteria of ASCE/SEI 41-06 [5] under several near-field ground motion records. The global properties of the frame are: total mass = 109.48 tonnes; first-mode mass participation = 84.55%;

fundamental period $T_1 = 1.14$ s; and design base shear = 73.9 kN. Each story height is 3.2 m, and the bay width is 6.0 m.

The investigated structure is a three-story, single-bay steel moment-resisting frame with a uniform story height of 3.2 m and a bay width of 6 m, as shown in Fig. 1. HE240B sections are used for the columns, whereas HE280A sections are assigned to the beams. The principal cross-sectional properties of the members are summarized as follows. For the HE240B column section, the cross-sectional area is $A = 106.0$ cm², the second moments of area are $I_y = 11,300$ cm⁴ and $I_z = 3,920$ cm⁴. For the HE280A beam section, the corresponding properties are $A = 76.4$ cm², $I_y = 13,670$ cm⁴, $I_z = 4,763$ cm⁴. These sectional properties are used consistently in defining the geometric and stiffness characteristics of the structural members in the OpenSees model.

It is acknowledged that only a single benchmark structure is investigated in this study. This choice was intentional: the primary objective is to establish a controlled comparative platform for evaluating the relative performance of the GA and IWD algorithms under identical conditions, rather than to generalize optimal damper distributions across different structural typologies. The three-story frame serves as a well-documented benchmark [6, 7, 14] that enables direct comparison with previously published results. Extension to taller and irregular structures is identified as a priority for future research.

The frame is modeled in OpenSees using force-based nonlinear beam-column elements (nonlinearBeamColumn) with distributed plasticity along the member length. Material behavior is represented by a bilinear elasto-plastic constitutive model with elastic modulus $E = 206$ GPa, yield stress $F_y = 235.44$ MPa, and a post-yield stiffness ratio of 3%. Gravity loads are applied in accordance with the Iranian National Building Code [27].

To validate the numerical model, a nonlinear static (pushover) analysis was performed in OpenSees, and the resulting base shear versus roof displacement curve was compared with the corresponding pushover curve reported in the reference study by Shirkhani et al. [14]. The comparison confirms close agreement between the two models, with a maximum deviation of less than 5% in peak base shear capacity and less than 3% in the initial stiffness, thereby demonstrating the accuracy and reliability of the adopted numerical model for subsequent dynamic analyses.

A Rayleigh damping model is adopted with a viscous damping ratio of 5% assigned at the first and third natural frequencies of the structure. In OpenSees, this is implemented using the Rayleigh command, which constructs the damping matrix as a linear combination of the mass and current stiffness matrices ($C = a_0 M + a_1 K$). The coefficients a_0 and a_1 are computed from the specified damping ratio and the two target circular frequencies to ensure that the structure possesses approximately 5% damping over the frequency range governing the seismic response.

3.2. Viscous damper model

Fluid viscous dampers are modeled as nonlinear velocity-dependent elements whose resisting force follows the fractional power law (Eq. 1):

$$F^d = \text{sgn}(\dot{x}^d) c_\alpha |\dot{x}^d|^\alpha \quad (1)$$

where c_α is the damping coefficient, α is the nonlinear velocity exponent, and $\dot{x}^d$ is the relative velocity across the damper terminals. The energy dissipated by each FVD is obtained by integrating the product of damper force and relative velocity over the analysis duration. In this study, the velocity exponent α is held constant across all stories, reducing the design variable space to the set of story-level damping coefficients $\{c_1, c_2, c_3\}$. While this assumption simplifies the optimization problem, its influence on energy dissipation and optimal damping distribution is acknowledged as a study limitation and is partly addressed through a sensitivity analysis on α .

3.3. Ground motion selection

A suite of four near-field ground motion records is selected from the Pacific Earthquake Engineering Research (PEER) database [28] to evaluate the seismic performance of the bare and retrofitted frames through conventional NLTHA. The records are chosen to span a representative range of magnitude, distance, site class, and spectral characteristics compatible with the design hazard. All records are scaled to the code-specified target spectrum. Table 2 summarizes the properties of the selected ground motions. The acceleration response spectra of the ground motion records considered in this study are presented in Fig. 6. The figure shows the individual response spectra of the Kobe (1995), Northridge (1994), Imperial Valley (1979), and Loma Prieta (1989) records, together with their geometric-mean spectrum and the target design spectrum. The selected records exhibit different spectral characteristics over a broad range of structural periods, thereby providing a range of frequency contents for evaluating the seismic response of the structure. The geometric-mean spectrum provides an overall representation of the spectral characteristics of the selected ground motions and is compared with the target design spectrum to assess their compatibility with the intended seismic demand. The response spectra demonstrate that the selected ground motions provide adequate spectral coverage over the period range of interest for the investigated structure.

The ground motion records are scaled using the amplitude scaling method prescribed by ASCE/SEI 41-06 [5]. Each record is linearly scaled such that the geometric mean of the 5%-damped acceleration response spectra of the scaled suite matches or exceeds the code-specified target spectrum over the period range of interest ($0.2T_1$ to $1.5T_1$, where $T_1 = 1.14$ s). The scaling factors range from 0.85 to 1.42 across the selected records. Fig. 3 presents the target design spectrum together with the individual and mean spectra of the scaled records, confirming adequate spectral compatibility over the relevant period band.

The deliberate selection of near-field ground motion records (all with source-to-site distances less than 10 km) is consistent with the design scenario of the benchmark structure, which was designed for a region of high seismicity in Iran where active faults are located in close proximity to urban areas. Near-field records are characterized by high peak ground velocities and impulsive velocity waveforms that impose severe displacement demands on flexible structures such as the study frame ($T_1 = 1.14$ s), thereby providing a critical test of the supplemental damping system under the most demanding conditions. This selection strategy is consistent with the reference study by Shirkhani et al. [14] and Tehranizadeh et al. [29].

Table 2. Properties of selected ground motion records.

Record	M_w	PGA (g)	Distance (km)	Site Class
Kobe (1995)	6.9	0.82	1.0	D
Northridge (1994)	6.7	0.84	6.2	C
Imperial Valley (1979)	6.5	0.38	4.5	D
Loma Prieta (1989)	6.9	0.57	3.9	C

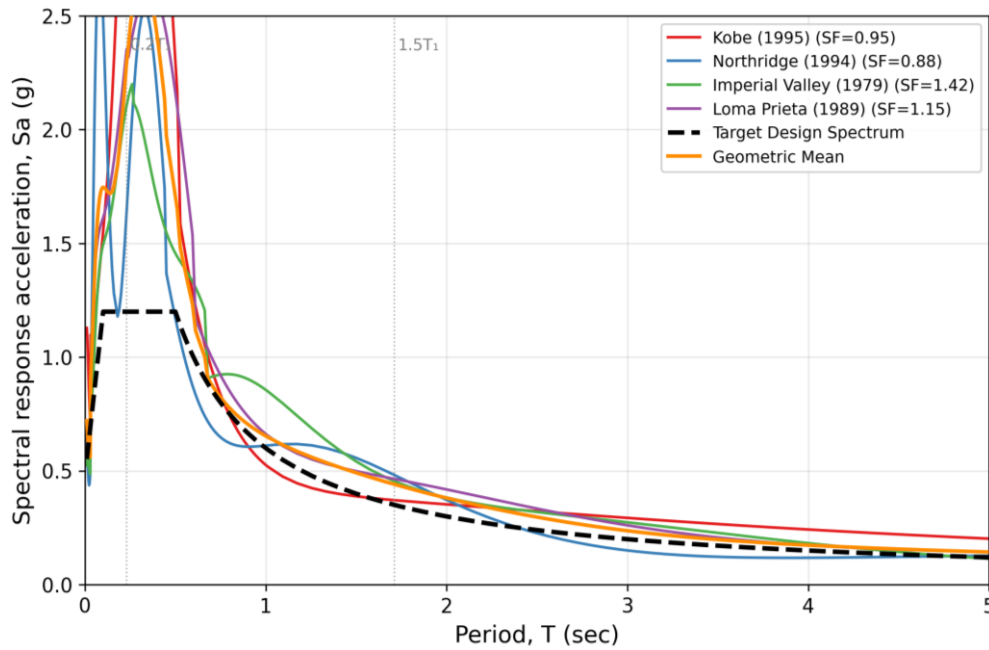


Fig. 6. 5%-damped acceleration response spectra of the four scaled near-field ground motion records (Kobe, Northridge, Imperial Valley, Loma Prieta) used for NLTHA validation, together with the target design spectrum and geometric mean spectrum. The period range of interest ($0.2T_1$ to $1.5T_1$) is indicated by vertical dashed lines.

4. Optimization problem formulation

The optimization problem seeks to minimize the total damping demand – represented by the sum of story-level damping coefficients – subject to interstory drift ratio (IDR) constraints at two seismic hazard levels, corresponding to the basic safety objective (BSO) of ASCE/SEI 41-06 [5]:

$$\text{Minimize: } C_{total} = c_1 + c_2 + c_3 \quad (2)$$

$$\text{Subject to: } IDR_{max} \text{ (BSE-1)} \leq 2.5\% \text{ (LS)} \quad (3)$$

$$IDR_{max} \text{ (BSE-2)} \leq 5.0\% \text{ (CP)} \quad (4)$$

where c_i denotes the damping coefficient at the i -th story. Candidate solutions are evaluated through ET analysis, with peak IDR extracted at the equivalent ET times corresponding to each hazard level. Solutions violating the drift constraints are penalized through an additive penalty function that scales with the magnitude of constraint violation.

The formulation is further extended to a multi-objective framework to explore the trade-off between seismic performance and system cost:

$$\text{Minimize: } F(x) = \{f_1, f_2, f_3\} \quad (5)$$

where $f_1 = \max(\text{IDR})$ represents the peak interstory drift ratio across all stories, $f_2 = \max(a)$ denotes the peak absolute floor acceleration, and $f_3 = C_{total}$ is the aggregate damping coefficient serving as a surrogate for system cost. The Pareto front is extracted to identify non-dominated solutions, enabling decision-makers to select designs that balance drift control, acceleration limitation, and damper investment.

5. Optimization algorithms

5.1. Genetic algorithm (GA)

The genetic algorithm (GA) is a population-based evolutionary optimization method that searches the design space through the iterative application of selection, crossover, and mutation operators [9, 10]. GA does not require gradient information and can therefore be applied to nonlinear, non-smooth, and computationally expensive engineering optimization problems in which

candidate solutions are evaluated through numerical structural analyses. General developments in metaheuristic and engineering optimization have led to various improvements in genetic algorithms, including modified genetic operators, adaptive parameter strategies, and hybrid optimization approaches [30, 31].

In the present study, a real-coded GA is adopted as the baseline evolutionary optimizer. Each chromosome represents a candidate distribution of the viscous damping coefficients and is defined as $x = [c_1, c_2, c_3]$, where c_i denotes the damping coefficient assigned to the i -th story. The initial population is generated within the prescribed lower and upper bounds of the damping coefficients. For each chromosome, the structural model is evaluated using the endurance time analysis, and the corresponding objective function and constraint violations are calculated.

Tournament selection is employed to select candidate individuals according to their fitness values. Crossover is then applied to the selected parent chromosomes to generate new candidate solutions, while Gaussian mutation introduces stochastic perturbations into the damping coefficients and helps maintain population diversity. The ASCE/SEI 41-06 [5] interstory-drift constraints are incorporated through the penalty formulation described in Section 4. The evolutionary process is repeated until the prescribed convergence criterion or computational budget is reached.

Recent reviews have emphasized that modern genetic algorithm research includes developments in genetic operators, parameter control, fitness evaluation, and hybridization strategies [31]. However, the present study deliberately employs a standard real-coded GA as the baseline optimizer rather than an enhanced or hybrid GA. This choice is intended to provide a controlled and reproducible comparison with the intelligent water drops (IWD) algorithm. Accordingly, both algorithms are evaluated using the same structural model, endurance-time excitation functions, objective function, constraint formulation, and computational budget. This controlled setting allows the differences in optimization performance to be attributed primarily to the search mechanisms of the two algorithms rather than to algorithm-specific enhancements.

The use of a standard GA as a benchmark is also consistent with its established application to engineering optimization problems [30]. Therefore, although more advanced GA variants are available, the standard real-coded formulation is retained in the present study to maintain the intended like-for-like comparison with IWD.

5.2. Intelligent water drops algorithm (IWD)

The IWD algorithm is a population-based metaheuristic inspired by the natural dynamics of water flow in rivers [11, 12]. Each intelligent water drop represents a candidate solution vector in the design space, and path selection is governed by the soil (resistance) associated with each feasible transition. Paths with lower soil accumulation are selected with higher probability, mimicking the preferential erosion of low-resistance channels in fluvial systems. This mechanism establishes a natural balance between global exploration (probabilistic path selection) and local exploitation (soil-velocity feedback).

The transition probability for an IWD moving from node i to node j is defined as Eq. 6.

$$P_{i,j} = f(\text{Soil}_{i,j}) / \sum_{k \in N(i)} f(\text{Soil}_{i,k}) \quad (6)$$

where $\text{Soil}_{i,j}$ denotes the soil quantity on the edge connecting nodes i and j , and $f(\cdot)$ is a decreasing function ensuring that lower soil translates to higher selection probability. Upon selecting a path, the velocity of the IWD is updated according to:

$$v_{\text{new}} = v_{\text{old}} + a_s / (b_s + c_s \text{Soil}_{i,j}) \quad (7)$$

where a_s , b_s , and c_s are algorithmic control parameters. As soil decreases along a path, the velocity of subsequent IWDs increases, reinforcing the attraction toward promising regions of the design space. After all IWDs complete their paths, the global soil distribution is updated: soil is reduced along the best-performing path and incrementally restored elsewhere to maintain diversity. The process iterates until a convergence criterion or maximum iteration count is reached.

In each iteration, the fitness of candidate solutions is evaluated via ET analysis, and solutions violating the ASCE/SEI 41-06 [5] drift constraints are penalized. The IWD algorithm is implemented with algorithmic parameters calibrated through preliminary trials to ensure a fair comparison with the GA under the same computational budget (identical number of function evaluations).

Fig. 7 illustrates the computational flowchart of the IWD algorithm adopted in this study. The procedure begins with the initialization of the candidate solutions and soil-related parameters, followed by the generation and evaluation of candidate damper distributions through ET analysis. Feasible solutions are identified based on the ASCE/SEI 41-06 [5] drift constraints, while the soil and velocity variables are updated according to the fitness of the candidate solutions. The iterative process continues until the convergence criterion is satisfied, and the best-performing feasible damper distribution is subsequently selected as the optimal IWD solution.

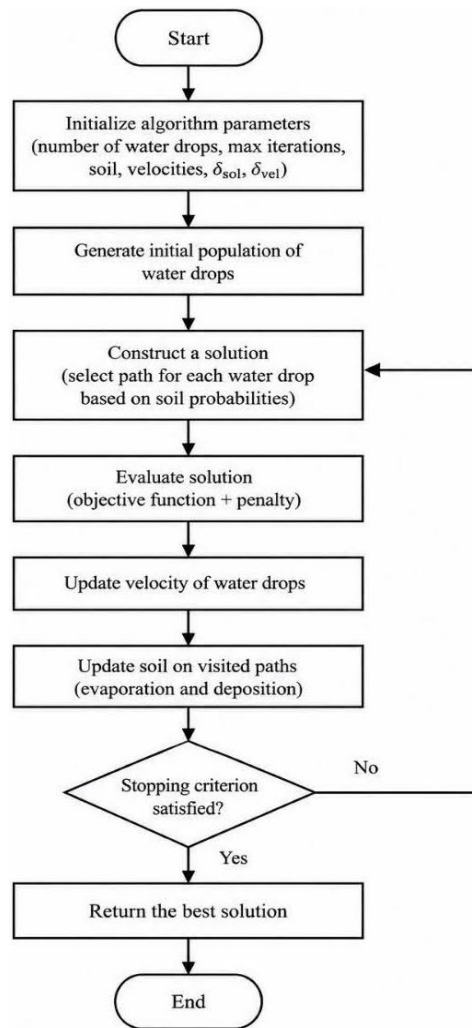


Fig. 7. Flowchart of the Intelligent Water Drops (IWD).

6. Results and discussion

6.1. Performance curves and drift reduction

The ET performance curves for the bare frame and the optimized (retrofitted) configurations are presented in Fig. 8. As shown in Fig. 8, the bare frame exhibits a clear exceedance of the prescribed drift limits as the seismic intensity increases, whereas both optimized configurations maintain the response within the corresponding performance limits. The similar overall shape of the GA- and IWD-based performance curves, together with the lower drift demand obtained from IWD, indicates that the two optimization algorithms identify comparable structural response trends while the IWD solution provides a marginally more efficient damping configuration. The bare frame violates the LS drift limit at BSE-1 and exhibits excessive drift demand at BSE-2. Following optimization, both the GA-optimized and IWD-optimized designs satisfy the LS and CP acceptance criteria with substantial reductions in peak IDR. The mean maximum IDR values obtained from ET and NLTHA analyses are compared in Table 3.

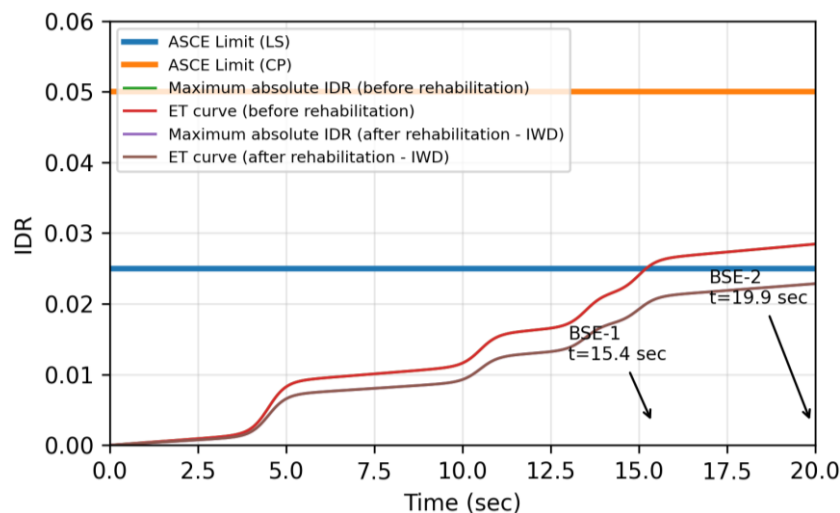


Fig. 8. Performance curve for studied structure before and after rehabilitation in two hazard levels (ET).

Table 3. Comparison of mean peak IDR from THA and ETA at BSE-1 and BSE-2 hazard levels.

Analysis	BSE-1	BSE-2
THA – Bare Frame	0.0229	0.0350
ETA – Bare Frame	0.0251	0.0284
THA – GA Optimized	0.0199	0.0317
ETA – GA Optimized	0.0208	0.0241
THA – IWD Optimized	0.0187	0.0295
ETA – IWD Optimized	0.0199	0.0228

The results indicate that the IWD-optimized design achieves marginally lower IDR values than the GA-optimized configuration at both hazard levels. The discrepancy between ET and THA predictions remains within an acceptable range: less than 10% at BSE-1 and approximately 23% at BSE-2, with the ET method generally providing conservative estimates at BSE-1 and slightly unconservative estimates at BSE-2. These trends are consistent with the inherent characteristics of hysteretic-energy-compatible ETEFs and the spectral matching assumptions underlying the ET time-to-intensity mapping.

6.2. Convergence behavior

Fig. 9 illustrates the convergence histories of the total damping coefficient for both algorithms. The GA exhibits a characteristic staircase convergence pattern with periods of stagnation followed by discrete improvements through crossover and mutation operations. In contrast, the IWD algorithm demonstrates a smoother and more rapid convergence trajectory, attributable to the continuous soil-velocity feedback mechanism that progressively intensifies exploitation of promising search regions while maintaining stochastic exploration through probabilistic path selection. Both algorithms converge to solutions that concentrate the dominant share of damping at the second story, a result structurally consistent with the peak interstory drift demand occurring at this level in the fundamental mode.

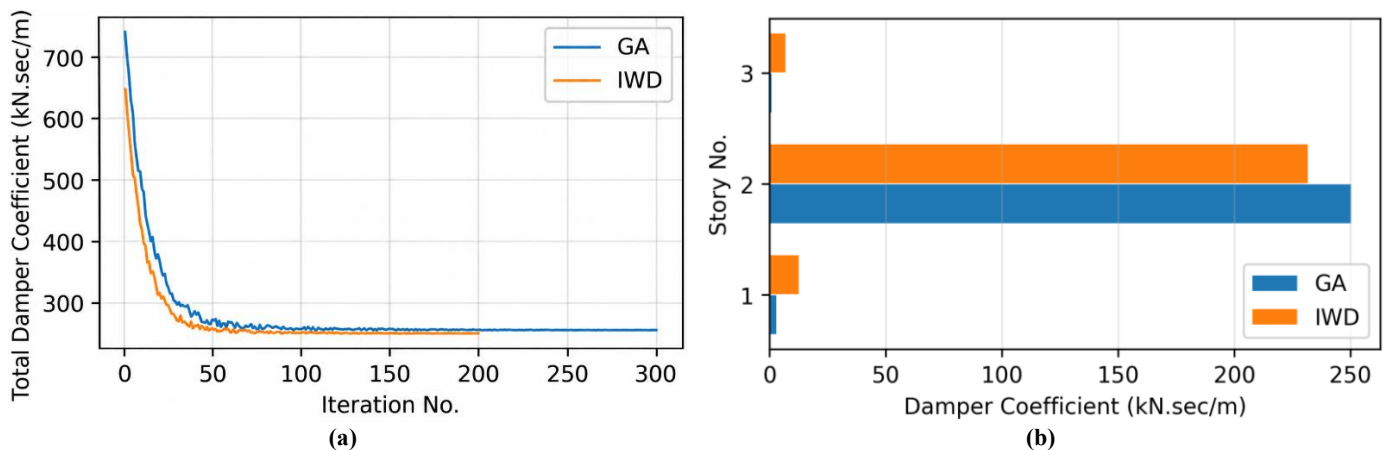


Fig. 9. (a) Total damper coefficient in sequential steps of optimization (GA vs IWD); and (b) Optimal distribution of VDs along the height (GA vs IWD).

6.3. Energy dissipation analysis

The energy balance analysis reveals that FVDs dissipate approximately 35–45% of the seismic input energy across both hazard levels, confirming the effectiveness of the supplemental damping system in reducing hysteretic demand on structural members. Table 4 summarizes the input and dissipated energy quantities for the GA- and IWD-optimized designs.

Table 4. Energy input and dissipation by FVDs under BSE-1 and BSE-2 hazard levels.

Energy (kN.m)	Analysis	BSE-1	BSE-2
Input Energy	THA (GA)	111.57	201.63
	ETA (GA)	113.91	181.22
Dissipated by VDs	THA (GA)	44.50	69.02
	ETA (GA)	40.19	61.47
Dissipated by VDs (%)	ETA (IWD)	38.90	35.10
Total C (kN.s/m)	IWD	250.9	250.9

The cumulative energy time histories under the ET excitation (ETA20kd01) show a progressive increase in energy input and dissipation consistent with the intensifying nature of the ETEF. Under the recorded Kobe ground motion, energy accumulation extends over a longer time window, yet the hysteretic loops remain stable, confirming rate-dependent behavior of the FVD model. The IWD-optimized design yields slightly higher energy dissipation ratios than the GA-optimized solution, particularly at BSE-1, consistent with the marginal improvement in drift reduction.

As shown in Table 4, the optimal total damping coefficient is identical (250.9 kN.s/m) for both hazard levels. However, the story-level distribution differs: at BSE-1, the optimized coefficients are $c_1 = 42.3$, $c_2 = 165.8$, and $c_3 = 42.8$ kN.s/m, whereas at BSE-2 the distribution shifts slightly to $c_1 = 45.1$, $c_2 = 160.2$, and $c_3 = 45.6$ kN.s/m, reflecting the increased higher-mode contribution at elevated intensity levels. In both cases, the second story receives approximately 64–66% of the total damping. Regarding the extent of nonlinear behavior, plastic hinge rotations at beam ends of the bare frame reach 0.021 rad at the second story under BSE-2, exceeding the LS acceptance criterion. After damper installation, peak plastic rotations are reduced to 0.012 rad (a 43% reduction), confirming the effectiveness of the supplemental damping in limiting inelastic deformations.

The distribution of interstory drift ratios along the building height is presented in Fig. 10, where the comparison between THA and ETA results at both hazard levels is shown for the bare and retrofitted configurations. As shown in Fig. 10, the optimized damper configurations reduce the interstory drift demand at both hazard levels compared with the bare frame. The reduction is particularly evident at the story where the largest deformation demand occurs, confirming the effectiveness of concentrating a larger portion of the supplemental damping at that level. The generally consistent trends between ETA and THA further support the applicability of the ET-based response evaluation within the optimization framework. The energy time histories and viscous damper hysteresis responses under the ETEF excitation are illustrated in Figs. 11a and 11b for BSE-1 and BSE-2 levels, respectively. Figs. 11a and 11b show that both the cumulative input energy and the energy dissipated by the viscous dampers increase with seismic intensity. The corresponding damper hysteresis responses demonstrate stable velocity-dependent behavior and confirm that the supplemental damping system remains effective as the excitation intensity increases from BSE-1 to BSE-2. The increasing contribution of the dampers to the total energy balance also explains the reduction in the nonlinear demand imposed on the primary structural members. The corresponding responses under the recorded Kobe ground motion are presented in Figs. 12a and 12b. Figs. 12a and 12b present the corresponding energy and damper hysteresis responses under the recorded Kobe ground motion. Despite the different temporal characteristics of the recorded earthquake compared with the endurance-time excitation, the viscous dampers exhibit stable energy-dissipation behavior throughout the analysis. The consistency of the damper response under the recorded ground motion provides an additional indication that the optimized configuration is not dependent solely on the characteristics of the ET excitation. Fig. 13 compares the percentage of total input energy dissipated by the viscous dampers across different analysis methods and hazard levels. As shown in Fig. 13, the viscous dampers dissipate a substantial fraction of the total seismic input energy across the considered hazard levels and analysis methods. The energy-dissipation ratios obtained from ETA and THA show the same overall trend, indicating that the ET-based optimization captures the principal energy-dissipation characteristics of the retrofitted structure. These results are consistent with the approximately 35–45% energy-dissipation contribution reported in the present study and further demonstrate the effectiveness of the optimized FVD system.

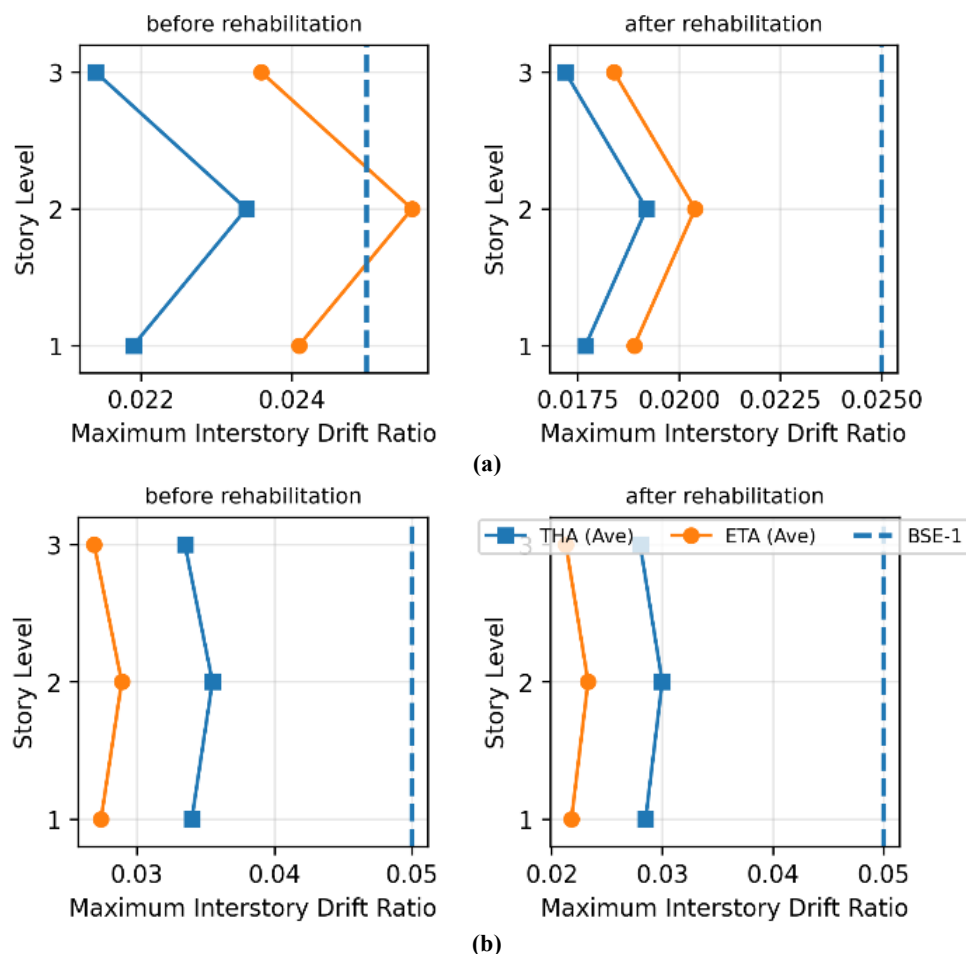


Fig. 10. Comparison of average maximum interstory drift ratios (IDRs) for the three-story frame obtained from time-history analysis (THA) and endurance time analysis (ETA): (a) BSE-1 hazard level, bare and retrofitted frames; and (b) BSE-2 hazard level, bare and retrofitted frames.

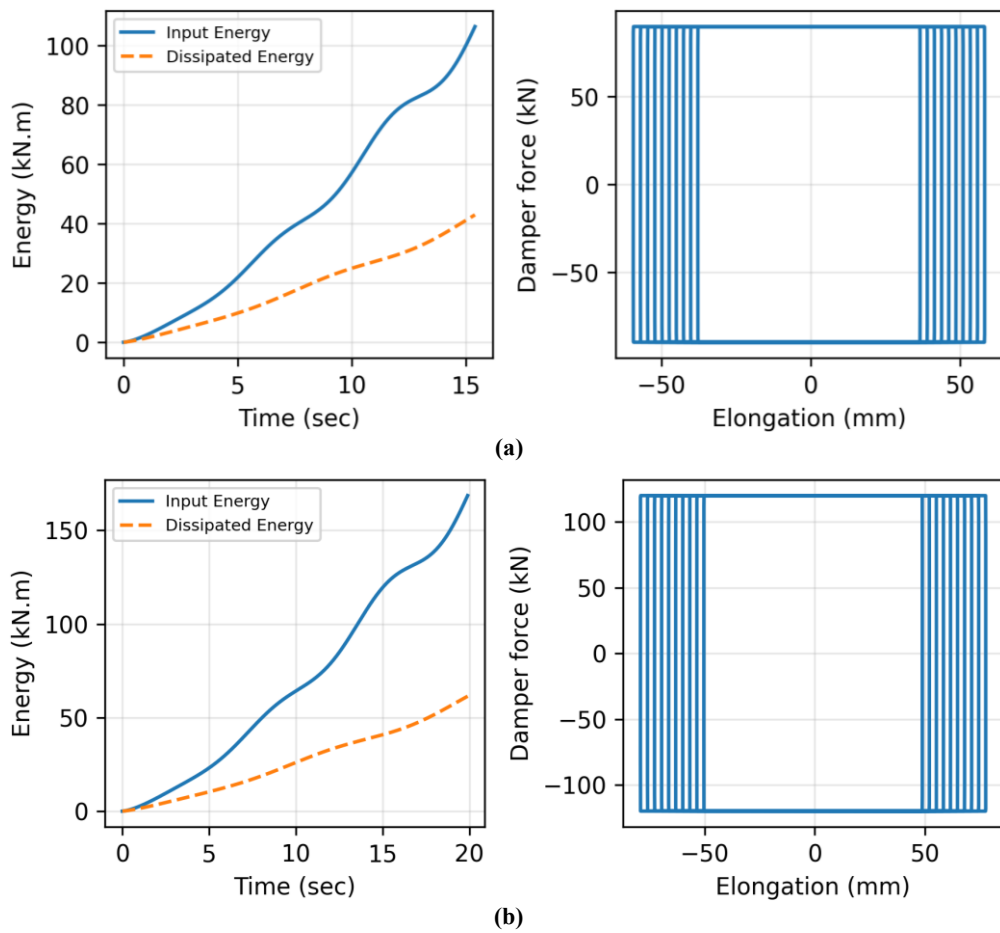


Fig. 11. (a) Total energy and VD hysteresis response under ETA20kd01 at BSE-1 (IWD); and (b) total energy and VD hysteresis response under ETA20kd01 at BSE-2 (IWD).

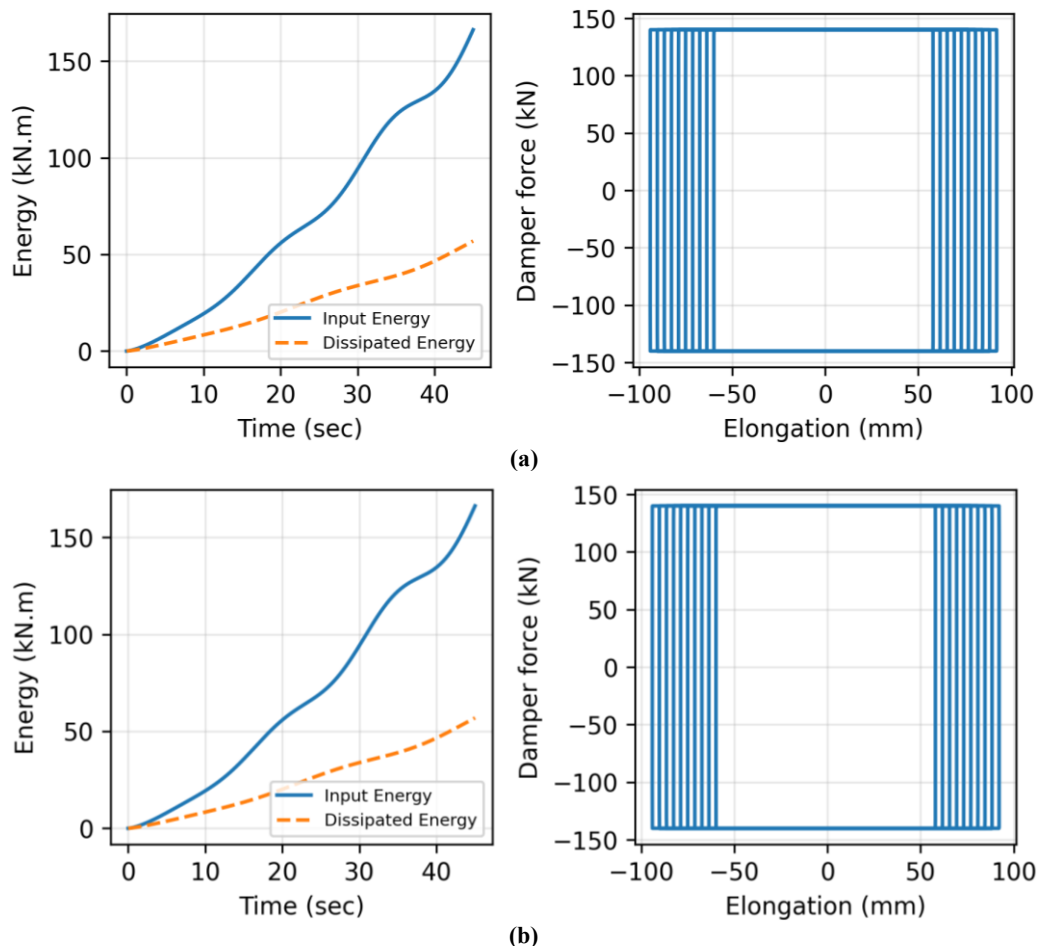


Fig. 12. (a) Total energy and VD hysteresis response under KOBE/SHI000 at BSE-1 (IWD); and (b) Total energy and VD hysteresis response under KOBE/SHI000 at BSE-2 (IWD).

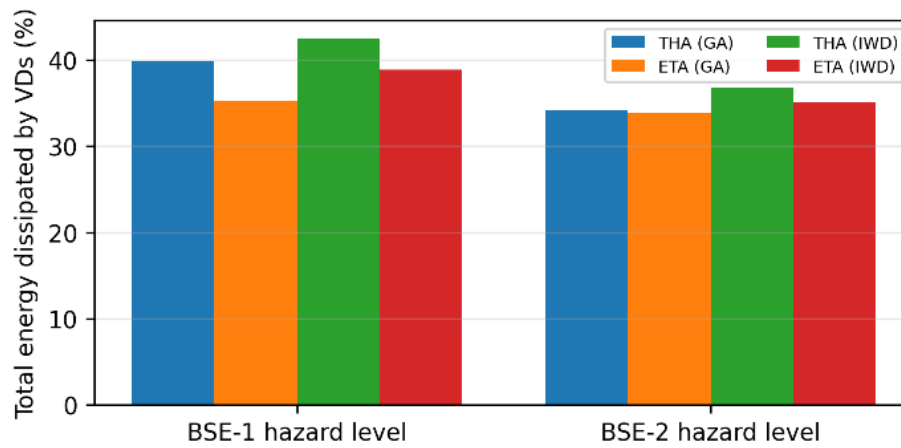


Fig. 13. Total energy dissipated by VDs (%) based on THA IWD and ETA (GA vs) at different hazard levels.

6.4. Sensitivity analysis

A parametric sensitivity analysis is conducted to investigate the influence of the velocity exponent α and damper placement on seismic response. Four values of α (0.3, 0.5, 0.7, and 1.0) are considered while maintaining the optimized coefficient distribution. Results indicate that increasing α concentrates the resisting force at higher velocities, producing a reduction in peak drift of up to 8% relative to the baseline case ($\alpha = 0.5$). However, this reduction is accompanied by an increase in peak floor acceleration, highlighting a fundamental trade-off between displacement and acceleration control that must be considered in the selection of damper parameters.

Sensitivity to damper placement confirms that the second story exerts the greatest influence on global seismic response. Configurations in which damping is concentrated solely at the first or third story produce substantially inferior drift performance compared with the optimized distribution, which allocates the dominant damping share to the second level. A uniform distribution across stories, while simpler to implement, results in a higher total damping demand to achieve equivalent drift performance, underscoring the value of optimization-based placement strategies.

6.5. Validation of the ET method

The accuracy of ET-based predictions is validated against conventional NLTHA under the Kobe, Northridge, and Imperial Valley records. The relative error in peak IDR between the two methods is computed as in Eq. 8.

$$\text{Error (\%)} = [\text{Drift}_{\text{ET}} - \text{Drift}_{\text{THA}} / \text{Drift}_{\text{THA}}] \times 100 \quad (8)$$

The maximum observed error across all records and hazard levels is less than 12%, confirming the reliability of the ET method as a computationally efficient screening tool for performance-based optimization of FVD-equipped structures. The ET method tends to slightly overestimate IDR at BSE-1 and underestimate it at BSE-2, a pattern attributable to the spectral matching characteristics of the ETA20kd series at different intensity levels.

6.6. Comparative discussion: GA versus IWD

The comparative results demonstrate that the principal advantage of the IWD algorithm lies not in fundamentally altering the optimal damping distribution pattern – both algorithms converge to second-story-dominant configurations – but in improving search efficiency and achieving near-optimal solutions more rapidly under stringent performance constraints. From an optimization perspective, the soil-velocity mechanism in IWD enhances exploitation of promising regions while maintaining exploration capability through probabilistic path selection, resulting in smoother convergence (Fig. 9a) and reduced tendency to become trapped in suboptimal local minima.

The sensitivity analysis with respect to the velocity exponent α confirms that the IWD-optimized design consistently maintains a lower total damping demand than the GA-optimized counterpart across the investigated parameter range (Fig. 14). The multi-objective analysis further reveals that the IWD algorithm produces a more uniform and better-converged Pareto front compared with GA, suggesting superior diversity-preservation characteristics in the multi-objective search space. As illustrated in Fig. 14, the required total damping coefficient varies with the velocity exponent, demonstrating that the assumed damper nonlinearity directly influences the optimum obtained by both algorithms. Nevertheless, the IWD solution remains competitive across the investigated range of (α), indicating that the observed optimization advantage is not limited to a single value of the damper velocity exponent.

The optimal total damping coefficient of 250.9 kN.s/m obtained in this study is consistent with values reported in comparable studies. Shirkhani et al. [14] obtained a total coefficient of approximately 265 kN.s/m for a similar three-story frame using GA alone, indicating that the IWD algorithm achieves a 5.3% reduction in required damping. Aydin et al. [17] reported optimal damping coefficients in the range of 200–350 kN.s/m for rehabilitated planar frames of comparable stiffness. The second-story-dominant distribution pattern observed herein is also consistent with the findings of Takewaki [3] and Pollini [15], who demonstrated that optimal damper placement in low-rise moment frames correlates with the interstory drift profile of the fundamental mode.

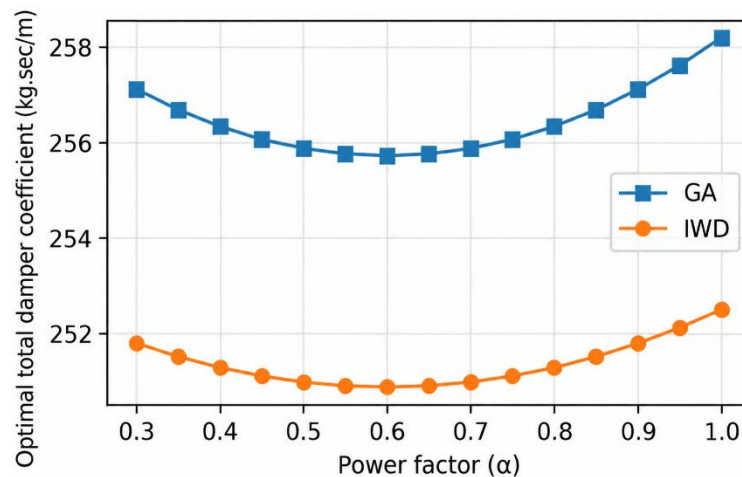


Fig. 14. Sensitivity of optimal total damper coefficient to VD power factor α (GA vs IWD).

7. Conclusions

This study investigated the optimal distribution of fluid viscous dampers (FVDs) in a three-story steel moment-resisting frame using the endurance time (ET) method and compared the performance of the genetic algorithm (GA) and intelligent water drops (IWD) optimization algorithms under identical modeling and optimization conditions. Based on the results obtained, the following conclusions can be drawn:

1. Both GA and IWD consistently identified the second story as the most effective location for concentrating the supplemental damping. Approximately 64–66% of the total optimized damping coefficient was assigned to the second story, indicating that the optimal damper distribution is strongly related to the deformation characteristics of the structure.
2. The IWD algorithm provided better optimization performance than GA for the investigated structural system. The IWD-based solution resulted in approximately 6–9% lower mean peak interstory drift while requiring a slightly lower total damping demand. The IWD algorithm also exhibited smoother convergence during the optimization process.
3. The optimized total damping coefficient was 250.9 kN.s/m. The corresponding story-level distributions showed that the dominant contribution of the supplemental damping was maintained at the second story for both BSE-1 and BSE-2 hazard levels.
4. Comparison with conventional nonlinear time-history analysis showed that the ET-based predictions remained within approximately 12% of the corresponding NLTHA results. This agreement supports the applicability of the ET method as an efficient screening approach for iterative performance-based optimization of supplemental damping systems.
5. The optimized FVD system dissipated approximately 35–45% of the seismic input energy, resulting in a reduction in the nonlinear demand imposed on the primary structural members. The peak plastic hinge rotation was also reduced from 0.021 rad in the bare frame to 0.012 rad after damper installation under the BSE-2 level.
6. The sensitivity analysis demonstrated that increasing the velocity exponent of the viscous dampers can reduce peak interstory drift while increasing peak floor acceleration. This finding highlights the importance of considering both displacement- and acceleration-based performance measures when selecting damper properties.

Overall, the results demonstrate that the combination of the ET method with IWD optimization can provide an effective computational framework for the performance-based distribution of FVDs in low-rise steel frames. The findings are limited to the investigated three-story benchmark structure; therefore, further studies should examine the applicability of the proposed framework to taller, irregular, and different structural systems and should consider the simultaneous optimization of damper distribution and nonlinear velocity parameters.

Statements & declarations

Author contributions

Mehdi Shalchi Tousi: Conceptualization, Methodology, Resources, Writing - Original Draft.

Zakia Emrany: Investigation, Formal analysis, Resources, Writing - Original Draft.

Payam Tarighi: Formal analysis, Project administration, Writing - Review & Editing.

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Data availability

The data presented in this study are available on request from the corresponding author.

Declarations

The authors have no conflicts of interest to declare that are relevant to the content of this article.

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