Study of Seismic Response and Optimization of Control Forces For Magnetorheological Damper in 3D-Frame using AMGA-VEGA-MOGA with Fuzzy Controller

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ABSTRACT: This study investigates the reduction of seismic effects in three-dimensional framed structures using magnetorheological (MR) dampers integrated with intelligent control strategies. The research focuses on determining optimal control forces to minimize lateral displacement and inter-story drift under earthquake loading. Three genetic algorithms Adaptive and Modular Genetic Algorithm (AMGA), Vector Evaluation Genetic Algorithm (VEGA), and Multi-Objective Genetic Algorithm (MOGA) are individually combined with a fuzzy logic controller. Displacement and velocity are used as input parameters, while the control output regulates the voltage applied to the MR dampers, thereby adjusting their damping force in real time. A realistic 3D frame model representing part of an actual building, equipped with eight MR dampers and subjected to recorded ground acceleration histories, was developed and analyzed in MATLAB. Comparative evaluation of the hybrid controllers yielded reductions in both maximum floor drift (25.74%) and maximum RMS displacement (32.2%). The performance advantage in the Y-direction yielded the highest reductions for both floor drift (16.92%) and RMS displacement (33.45%). Overall, the primary objective is to recenter the building and reduce structural movements with the aid of these algorithms.

INTRODUCTION: Reinforced concrete (RC) buildings form the backbone of modern urban infrastructure and are widely used in civil and structural engineering projects. Earthquake-resistant design is a critical requirement for RC buildings to ensure safety, serviceability, and long-term durability under seismic loading. Seismic forces generated during earthquakes induce significant lateral displacements and inter-story drifts in multi-story buildings, which can lead to structural damage or even collapse. To address these challenges, structural control systems have been developed and applied in engineering practice: passive systems (e.g., base isolators, tuned mass dampers) dissipate energy without external power; active systems use external energy to apply counteracting forces in real time; and semi-active systems (MR Damper) combine the advantages of both, offering adaptability with lower energy demand.

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The idea of controlling how structures move is not new. Over 100 years ago, Milne demonstrated it with a simple experiment, showing that we could influence how buildings respond to forces. In the early 20th century, scientists developed the theory of linear systems and applied it to structural dynamics, making significant advances in controlling and stabilizing structures, especially large and complex ones. These ideas quickly found real-world applications: engineers began using them to protect bridges from vibrations and later applied them to tall buildings facing extreme events like earthquakes and storms.

SEMI-ACTIVE CONTROL AND MR DAMPERS

In the field of vibration mitigation, control systems are generally divided into three categories: passive, active, and semi-active. Passive systems (like standard shock absorbers) are reliable but cannot adapt to changing conditions. Active systems can adapt but require large amounts of external power and complex machinery.

Semi-active control systems offer an ideal middle ground. They can adjust their damping properties in real-time to respond to varying vibrations (such as those from an earthquake or heavy wind), but they do not require heavy power sources to operate. Because they only absorb energy and never push energy back into the structure, they are inherently safe and will not accidentally destabilize the system they are protecting.

One of the most promising and widely researched semi-active devices is the Magnetorheological (MR) damper. An MR damper is filled with a smart fluid containing microscopic iron particles. In its normal state, when there is no magnetic field, the iron particles float freely and the fluid behaves like normal oil. In its active state, when an internal electromagnet is turned on, the magnetic field forces the iron particles to align into chains, transitioning the fluid from a liquid to a semi-solid paste in milliseconds. By simply adjusting the electrical current sent to the electromagnet, the control system can instantly change how stiff or soft the damper is, providing highly customized, real-time protection to a structure while using only minimal electricity.

MATHEMATICAL MODEL OF THE MR DAMPER

The mathematical model that relates the strength of the MR damper with the applied speed and voltage is known as the phenomenological model and was proposed in 1997 by Spencer et al. (Spencer Jr et al. 1997). Fig. 1 presents an overview of this model, which consists of the original Bouc–Wen model with a damper placed in series and a parallel spring.

The force f generated by the damper is calculated by Eq. (1):

$$f = \alpha z + c_0 (\dot{x} - \dot{y}) + k_0(x - y) + k(x - x_0) \quad (1)$$

Where z is the evolutionary variable and was calculated according to Eq. (2):

$$\dot{z} = -\gamma \mid \dot{x} - \dot{y} \mid z \mid z \mid^{n-1} - \beta (\dot{x} - \dot{y}) |z|^n + A (\dot{x} - \dot{y}) \quad (2)$$

Where

$$\dot{y} = \frac{1}{(c_0 + c_1)} [\alpha z + c_0 \dot{x} + k_0(x - y)] \quad (3)$$

In this model k_1 is the stiffness of the damper, c_0 and c_1 are the viscous damping at long and low speeds respectively; k_0 is the stiffness of the damper at high speeds, and x is the relative displacement between the ends of the MR damper, $\dot{x}$ is the speed of the damper, y is the internal displacement of the damper, x_0 is the initial displacement of the spring; k_1, γ, β and A are the parameters that control the shape of hysteresis cycles in the Bouc–Wen model, α and n are parameters responsible for the internal state z and determine its coupling with the force f and its evolution.

The parameters α, c_0 and c_0 are functions that depend on the applied voltage and they are determined by Eqs. (4)–(7):

$\alpha = \alpha_a + \alpha_b u$ (4) $c_0 = c_{0a} + c_{0b} u$ (5) $c_1 = c_{1a} + c_{1b}$ (6) $\dot{u} = -\eta(u - v)u$ (7)

Where u, v and η are the input voltages, output voltages and the time constant for the first order filter, respectively.

The variables $\alpha_a, \alpha_b, c_{0a}, c_{0b}, c_{1a}, y, c_{1b}$ are fixed parameters that relate the force of the MR damper with the voltage.

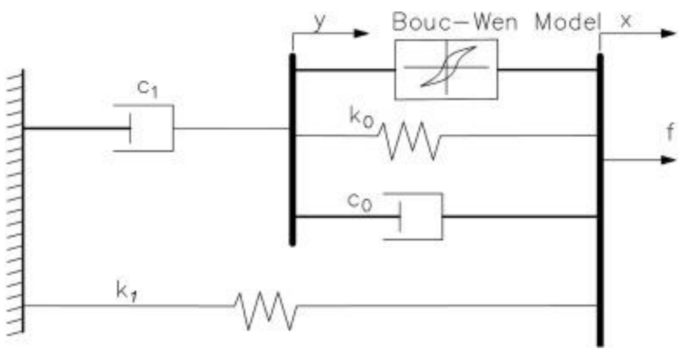


Figure 1. Definition of the phenomenological model for the MR damper (Spencer Jr et al. 1997).

Table 1. Parameters for the phenomenological model of the MR damper (Spencer Jr et al. 1997).

Parameter	Value	Unit	Parameter	Value	Unit
α_a	46.2	kN/m	k_1	0.485	kN/m
α_b	41.2	kN/m/V	γ	164.0	m^{-2}
c_{0a}	110	kN s/m	β	164.0	m^{-2}
c_{0b}	114.3	kN s/m/V	A	1107.2	—
c_{1a}	8359.2	kN s/m	n	2	—
c_{1b}	7482.9	kN s/m/V	η	2	s^{-1}
k_0	0.01	kN/m	x_0	0.0	m

MULTI-OBJECTIVE OPTIMIZATION (MOO)

Multi-objective optimization (MOO) is utilized to solve problems that contain two or more conflicting goals, where improving one objective inherently compromises another (Sellami et al. 2020). Designing MR damper systems is fundamentally a MOO problem, as it requires balancing competing factors like minimizing structural displacement, reducing acceleration, and controlling device costs. To manage this complexity, evolutionary algorithms specifically Genetic Algorithms (GAs) are frequently paired with Fuzzy Logic Controllers (FLCs). This combination enables adaptive, intelligent control without requiring exact mathematical models of the system (Yan and Zhou 2006).

Genetic Algorithms (GA)

A Genetic Algorithm (GA) is a robust optimization technique inspired by natural evolution (Wang and Sobey 2020). It excels in solving complex, non-linear problems where traditional gradient-based methods struggle or fall into local optima. Instead of evaluating a single solution, a GA evolves a population of potential candidate solutions across multiple generations. Core principles include: the fitness function, which evaluates and scores each candidate solution; selection, which prioritizes higher-fitness solutions as parents; crossover, which merges genetic material of two parents to create offspring; and mutation, which introduces slight, random variations maintaining genetic diversity (Tagtekin et al. 2021).

Multi-Objective Genetic Algorithm (MOGA)

Introduced by Fonseca and Fleming (1993), MOGA is designed to optimize multiple, conflicting objectives simultaneously. Instead of seeking one answer, MOGA identifies a Pareto front a spectrum of optimal trade-off solutions. The algorithm evaluates the population and assigns Rank 1 to all non-dominated individuals, iteratively sorting until every individual is ranked. Fitness values are then interpolated from these ranks, prioritizing lower-ranked (superior) solutions to guide the next evolutionary generation.

Vector Evaluated Genetic Algorithm (VEGA)

Introduced by Schaffer (1985), VEGA is an early, non-Pareto-based multi-objective algorithm. It modifies the standard genetic selection process by dividing the mating pool into k equal fractions, corresponding to k objectives. Each subpopulation is selected based on its performance in just one specific objective. VEGA's primary drawback is its tendency toward speciation favoring solutions that excel in a single objective but perform poorly in others, effectively finding extreme edges of the Pareto front but struggling to identify well-balanced compromise solutions (Kou et al. 2021; Mishra and Singh 2016).

Adaptive and Modular Genetic Algorithm (AMGA)

AMGA is an advanced framework that dynamically adjusts its genetic operators during the optimization process, rather than relying on fixed parameters (Ohira et al. n.d.; Kumari and Geethanjali 2017). Adaptive selection continuously monitors population fitness; if improvement stagnates, it automatically switches selection methods to alter selective pressure and help the population escape local optima. Modular co-evolution encodes the specific crossover and mutation operators directly into an individual's chromosome as extra genes, creating a co-evolutionary system where high-performing solutions and the most effective evolutionary strategies propagate simultaneously.

Fuzzy Logic Controllers (FLC)

Fuzzy logic provides a mathematical framework for reasoning with uncertainty by utilizing continuous degrees of truth (ranging from 0 to 1) rather than classical binary logic (Kiani and Nasrollahzadeh 2023). A Fuzzy Logic Controller (FLC) leverages this framework to execute control strategies based on linguistic IF-THEN rules. The operational cycle consists of four stages: (1) Fuzzification converts crisp numerical sensor inputs into fuzzy sets using predefined membership functions; (2) Rule Evaluation assesses fuzzified inputs against the established rule base to determine firing strength of each rule; (3) Implication uses firing strength to shape and scale the corresponding fuzzy output set; and (4) Defuzzification aggregates resulting fuzzy sets and translates them back into a single crisp numerical control command using techniques like the centroid method (Kim and Kang 2012; Liu et al. 2001).

PROPOSED METHODOLOGY

This study presents a comparative numerical analysis to optimize magnetorheological (MR) damper forces on a 3D structural model using hybrid genetic fuzzy algorithms (Bedoya-Zambrano et al. 2025; Lara-Valencia et al. 2022). The methodology is divided into four primary phases.

Structural Modeling. The study utilized an 11-story, 3D building frame (Medellín, Colombia) modeled with a rigid diaphragm (three degrees of freedom per floor) and Rayleigh damping. Eight large-scale MR dampers each modeled via the Bouc-Wen phenomenological model with a 20-ton maximum force capacity and a 0–10 V operating range were optimally installed on the 1st and 5th floors (Bathaei and Zahrai 2022; Masa'id et al. 2024).

Seismic Excitation. To evaluate 3D orthogonal effects, the structural model was subjected to eight historical earthquake records (including El Centro, Loma Prieta, and Kobe) featuring diverse frequency contents. All ground accelerations were applied at a 45-degree angle.

Design of Control Systems. Three parallel hybrid Fuzzy Logic Controllers (FLCs) were developed to calculate the required MR damper voltage. Each FLC utilizes first-floor displacement and velocity as inputs (scaled by 150 and 50, respectively) and features an inference system of 20 rules with Gaussian membership functions. FLC-1 employs VEGA, FLC-2 employs AMGA, and FLC-3 employs MOGA (Yan and Zhou 2006; Jung et al. 2003).

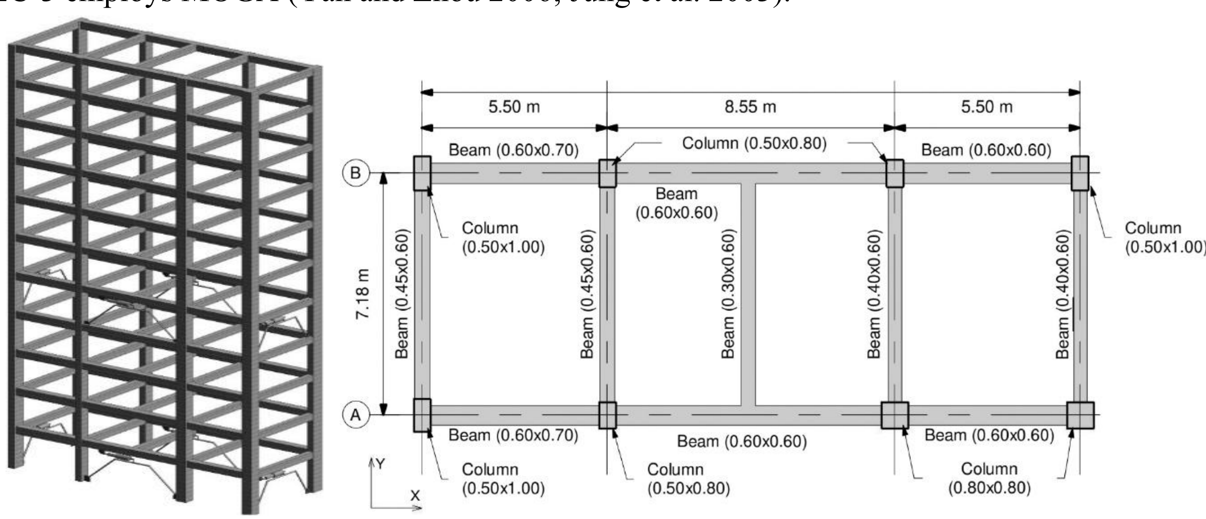


Figure 2. MR damper placement: plan and 3D model (Bedoya-Zambrano et al. 2025).

Optimization and Performance Evaluation. The genetic algorithms optimized the FLC parameters using a population of 50 individuals over 100 generations, with a crossover radius of 0.80 and a mutation radius of 0.10. The dual objective functions aimed to minimize both the maximum RMS displacement and the peak displacement response. The building's structural behavior was evaluated under four conditions (Uncontrolled, FLC-1, FLC-2, and FLC-3) to identify the most effective hybrid control strategy (Katebi et al. 2020; Jiang et al. 2022).

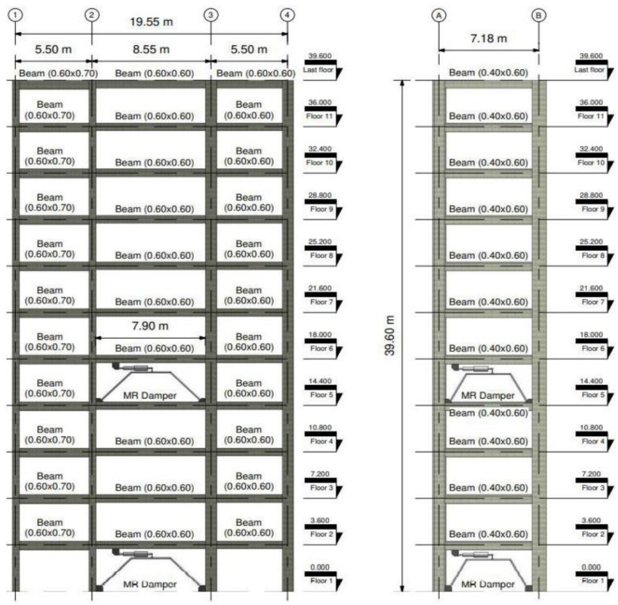


Figure 3. Geometrical data of building and MR damper placement: elevation (Bedoya-Zambrano et al. 2025).

Table 2. Definition of ground accelerations used in the study.

Earthquake	Year	Station	PGA [g]	Length [s]
El Centro	1940	El Centro	0.34	53.7
Morgan Hill	1984	C. Lake Dam	1.16	59.8
Petrolia	1992	C. Peak	1.14	60.0
Northridge	1994	Tarzana	1.78	60.0
Kobe	1995	Takatori	0.68	30.0

RESULTS: This study comparatively evaluated the effectiveness of three optimization algorithms MOGA, VEGA, and AMGA in mitigating the seismic response of a structure subjected to various earthquake ground motions. The results demonstrate that all three algorithms successfully reduced structural responses across all tested seismic loadings, proving their overall efficacy in structural control.

Table 3. Maximum floor drift in X direction.

Earthquake	Uncontrolled (m)	MOGA (m)	Red. (%)	VEGA (m)	Red. (%)	AMGA (m)	Red. (%)
Kobe	0.2425	0.1801	25.73	0.1942	19.92	0.1922	20.74
Morgan Hill	0.3091	0.2797	9.51	0.2985	3.43	0.2929	5.24
Northridge	0.2760	0.2391	13.37	0.2691	2.50	0.2603	5.69
El Centro	0.1343	0.1037	22.78	0.1174	12.58	0.1145	14.74
Petrolia	0.2019	0.1792	11.24	0.1936	4.11	0.1804	10.65

Table 4. Maximum floor drift in Y direction.

Earthquake	Uncontrolled (m)	MOGA (m)	Red. (%)	VEGA (m)	Red. (%)	AMGA (m)	Red. (%)
Kobe	0.1920	0.1658	13.65	0.1663	13.39	0.1595	16.93
Morgan Hill	0.2194	0.2088	4.83	0.2111	3.78	0.2051	6.52
Northridge	0.2397	0.2288	4.55	0.2387	0.42	0.2383	0.58
El Centro	0.0848	0.0813	4.13	0.0830	2.12	0.0845	0.35
Petrolia	0.1657	0.1557	6.04	0.1593	3.86	0.1548	6.58

Table 5. Maximum RMS value of X direction displacement.

Earthquake	Uncontrolled (m)	MOGA (m)	Red. (%)	VEGA (m)	Red. (%)	AMGA (m)	Red. (%)
Kobe	0.0410	0.0278	32.20	0.0284	30.73	0.0288	29.76
Morgan Hill	0.0437	0.0379	13.27	0.0394	9.84	0.0379	13.27
Northridge	0.0330	0.0304	7.88	0.0316	4.24	0.0296	10.30
El Centro	0.0181	0.0160	11.60	0.0162	10.50	0.0161	11.05
Petrolia	0.0283	0.0246	13.07	0.0258	8.83	0.0230	18.73

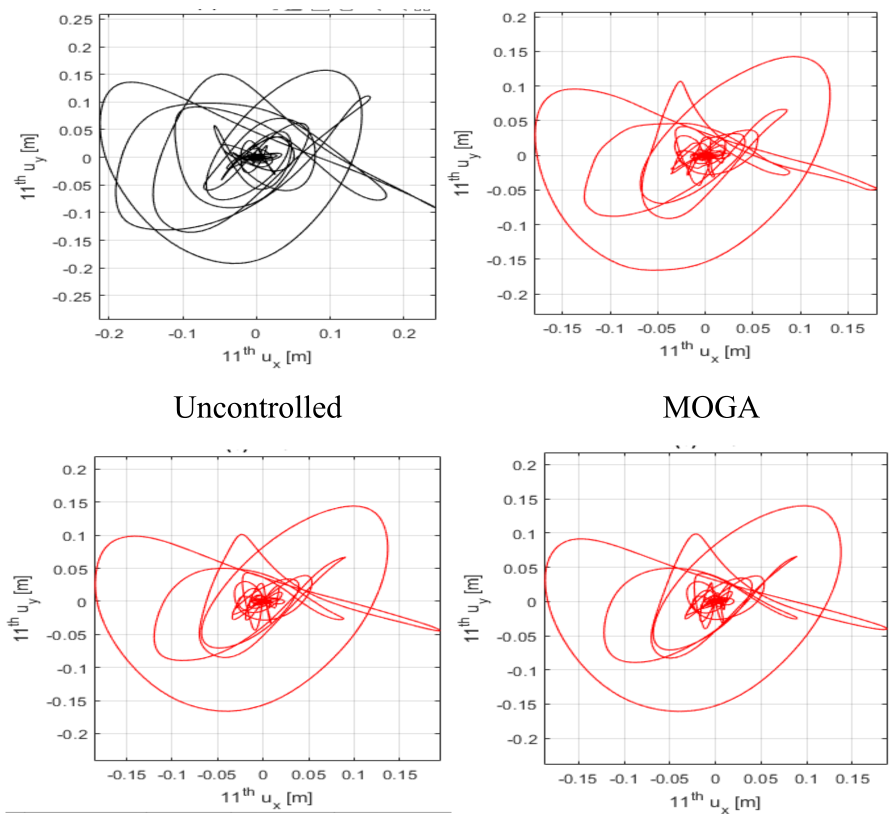
Table 6. Maximum RMS value of Y direction displacement.

Earthquake	Uncontrolled (m)	MOGA (m)	Red. (%)	VEGA (m)	Red. (%)	AMGA (m)	Red. (%)
Kobe	0.0308	0.0212	31.17	0.0213	30.84	0.0205	33.44
Morgan Hill	0.0316	0.0280	11.39	0.0288	8.86	0.0280	11.39
Northridge	0.0372	0.0339	8.87	0.0346	6.99	0.0345	7.26

El Centro	0.0146	0.0126	13.70	0.0118	19.18	0.0118	19.18
Petrolia	0.0206	0.0182	11.65	0.0181	12.14	0.0170	17.48

In the X-direction, MOGA consistently proved to be the most superior control strategy, achieving the highest overall reductions during the Kobe earthquake for both maximum floor drift (25.73%) and maximum RMS displacement (32.20%). Conversely, AMGA demonstrated a clear performance advantage in the Y-direction, yielding the highest reductions for both floor drift (16.93%) and RMS displacement (33.44%).

The following figures show the 11th story floor path (X–Y displacement orbit) for the Kobe earthquake under different control conditions.



Uncontrolled MOGA

VEGA AMGA

Figure 4. 11th story floor path of different control systems for Kobe earthquake: (a) Uncontrolled, (b) MOGA, (c) VEGA, (d) AMGA.

This directional dependence suggests that MOGA is better suited for dominating primary axis displacements, while AMGA effectively manages responses in the secondary axis. Ultimately, the findings indicate that utilizing MOGA and AMGA can consistently and significantly enhance structural safety and serviceability during seismic events. However, for maximum efficiency, the selection of the appropriate control algorithm must be carefully tailored to the dominant direction of the anticipated seismic forces.

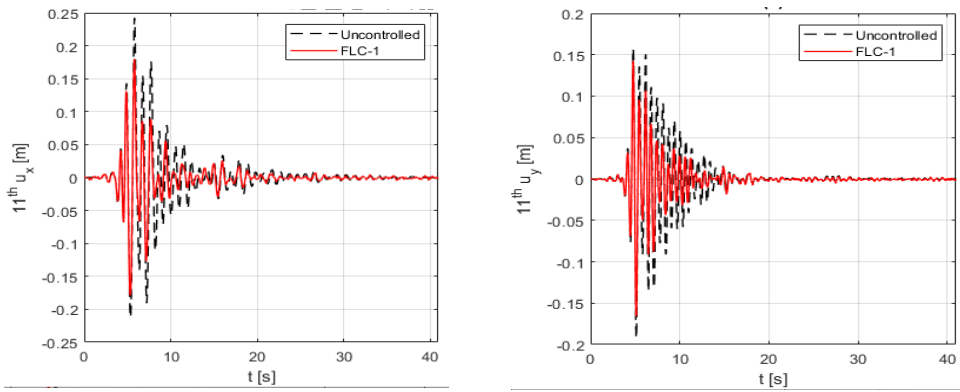


Figure 5. 11th floor displacement time history of MOGA for Kobe earthquake.

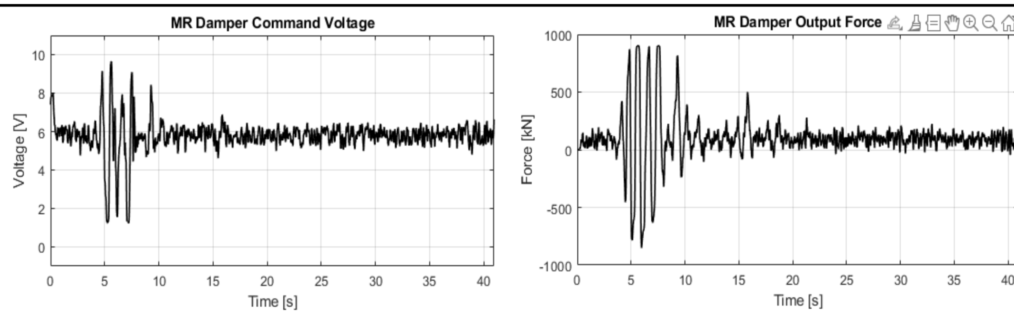


Figure 6. 11th floor displacement control signals of MOGA for Kobe earthquake.

CONCLUSION: This study comparatively evaluated the effectiveness of three optimization algorithms MOGA, VEGA, and AMGA in mitigating the seismic response of a structure subjected to various earthquake ground motions. The results indicate that algorithm efficacy for structural control is fundamentally tied to the specific dynamic properties of each principal axis; MOGA excels in controlling X-direction parameters, whereas AMGA is optimized for Y-direction responses.

X-Direction Performance Hierarchy. MOGA is the dominant algorithm for controlling maximum floor drift, consistently outperforming AMGA and VEGA across all five earthquake profiles. While MOGA remains the peak performer overall, AMGA occasionally achieves higher localized RMS displacement reductions (observed during the Northridge and Petrolia earthquakes).

Y-Direction Performance Hierarchy. AMGA generally dominates the Y-direction, yielding the highest overall reductions for both drift and RMS displacement across most seismic profiles, with MOGA typically taking the second position.

Exceptions to the Pattern. The established hierarchies are not absolute and demonstrate sensitivity to specific ground motions. In the Y-direction under Northridge and El Centro loadings, MOGA temporarily outperformed AMGA in drift reduction. Furthermore, during the El Centro earthquake, VEGA shifted from its typical baseline position to outperform AMGA, demonstrating the algorithms' sensitivity to specific frequency contents.

Ultimately, the findings indicate that utilizing MOGA and AMGA can significantly enhance structural safety and serviceability during seismic events. However, the selection of the appropriate control algorithm must be carefully tailored to the dominant direction of the anticipated seismic forces and the dynamic properties of the specific ground motion.

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