14th International Conference on Structural Safety and Reliability - ICOSSAR'25
1-6 June, 2025 - Los Angeles California, USA
R. Ghanem, E. Johnson, S. Masri and A. Olivier (Eds)

ADAPTIVE KRIGING MULTI-OBJECTIVE RELIABILITY-BASED DESIGN OPTIMIZATION OF FUZZY LOGIC CONTROLLER FOR MR DAMPER STRUCTURES

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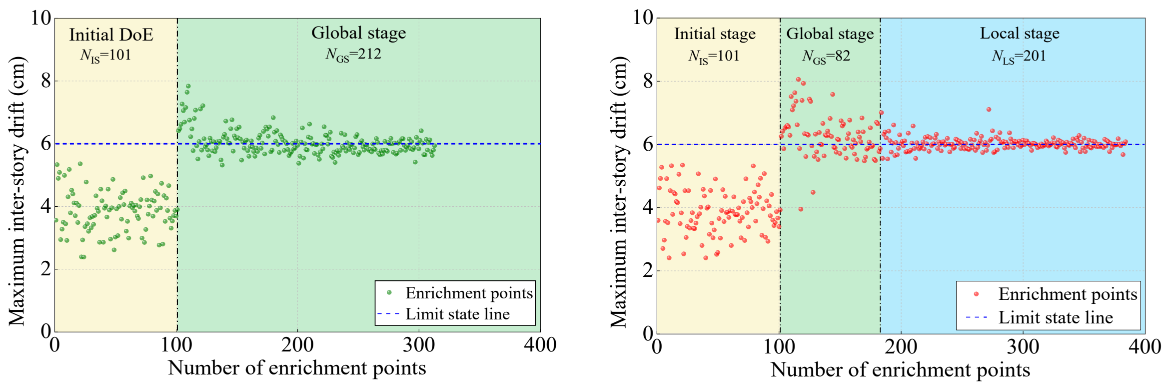
Key words: Reliability-based design optimization, Kriging, active learning, structural control, MR damper, fuzzy logic control.

Extended Abstract

Dynamic loads from natural hazards, such as severe earthquakes and strong winds, can induce excessive vibrations, displacements, and stresses in structures, potentially compromising their stability, functionality, and safety [1-2]. To mitigate these effects, magnetorheological (MR) dampers have emerged as effective semi-active control devices due to their ability to provide adjustable damping forces with rapid response times [3]. However, the presence of inherent uncertainties, including variations in structural properties, environmental conditions, and external loadings, poses significant challenges to the performance of MR dampers [4-5]. Addressing these uncertainties is crucial for ensuring the reliability and robustness of MR dampers in real-world applications [6]. Therefore, the development of advanced control strategies and optimization techniques is essential to enhance their adaptive capabilities, minimize failure risks, and improve overall structural safety in the face of unpredictable dynamic events.

To develop an optimal and reliable control system for MR damper-based structural systems, a fuzzy logic controller (FLC) is employed, and a reliability-based design optimization (RBDO) framework is formulated to determine the optimal FLC parameters. This framework aims to minimize two key objectives related to the inter-story drift and average control force while satisfying probabilistic constraints to account for uncertainties in dynamical system. Two RBDO methods are proposed to solve the RBDO problem. The first method combines a deterministic design optimization-based global Kriging model with the non-dominated sorting genetic algorithm (NSGA-II) to solve the multi-objective optimization problem, referred to as DDO-GK-MO. While this approach is effective, it operates within a deterministic framework for safety domain identification, which may suffer in terms of accuracy and computational efficiency when applied to complex uncertain systems. Building upon the DDO-GK-MO method, a two-stage multi-objective optimization (TS-MO) method introduces significant enhancements in precision, reliability, and efficiency. In the global stage, the Kriging surrogate model is iteratively refined by incorporating enrichment points distributed across the entire design space, enabling thorough exploration. In the local stage, the refinement process targets design points near the limit state function, utilizing a distance-refined U-learning function to improve accuracy in critical regions. Additionally, dynamic convergence criteria are implemented to strike an optimal balance between computational efficiency and solution accuracy.

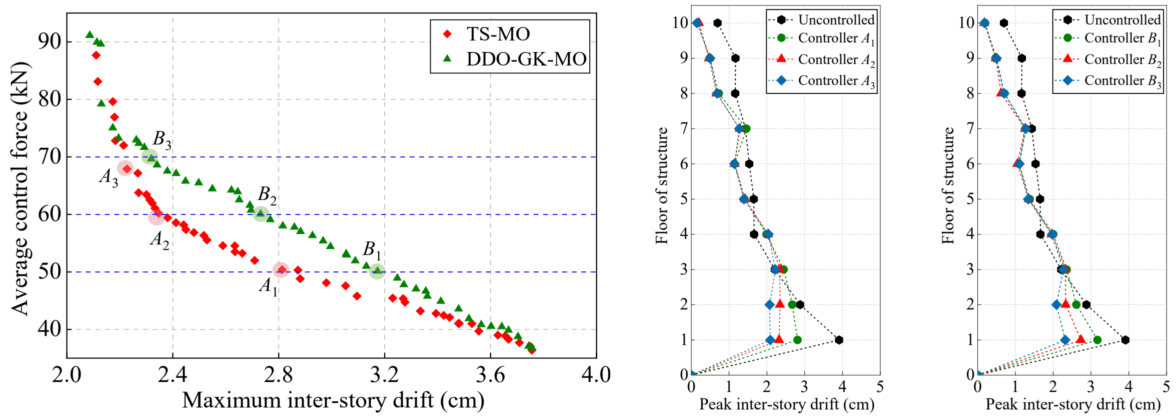
Both solution approaches are then employed to solve the RBDO problem for a FLC-driven MR damper-based structural system. Fig. 1 compares their respective metamodel training processes. In the DDO-GK-MO (Fig. 1(a)), the enrichment points in the initial stage are primarily located below the limit state line but progressively concentrate near the limit state line in the global stage as the design space is refined. In comparison, the proposed TS-MO approach (Fig. 1(b)) requires relatively more training points, but the enrichment points selected by this approach are more effective for training the Kriging surrogate, because the selected points are more concentrated in the vicinity of the limit state line.



22(a) DDO-GK-MO approach (b) TS-MO approach

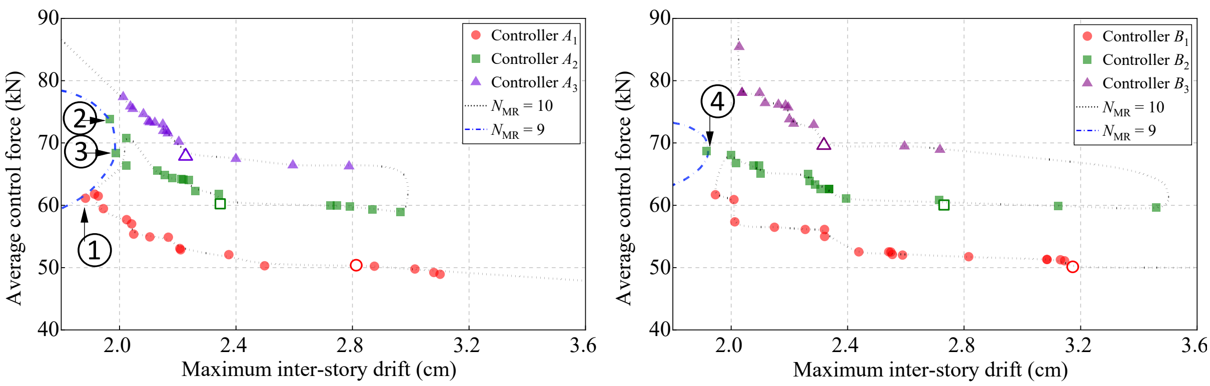
Fig. 1 Kriging model training processes

Fig. 2 compares the optimal Pareto fronts obtained from TS-MO and DDO-GK-MO. The Pareto front from TS-MO is closer to the origin, indicating superior control performance with lower control costs. This is because TS-MO explores the entire design space, whereas DDO-GK-MO operates within a reduced space derived from deterministic optimization, potentially excluding optimal solutions. To evaluate the structural seismic performance under the optimized FLCs, representative design solutions corresponding to different control force levels (F_{ave} = 50 kN, 60 kN, and 70 kN) are analyzed. Three solutions (A_1, A_2, A_3) from TS-MO and three (B_1, B_2, B_3) from DDO-GK-MO are selected to construct FLCs, as shown in Fig. 2(a). The seismic responses under these controllers are compared in Figs. 2(b) and (c). Both sets of controllers effectively reduce peak inter-story drift, particularly on lower floors where drift is significant. Higher control forces further decrease drift. However, Controllers A_1–A_3 yield smaller and more uniform drift responses than Controllers B_1–B_3, demonstrating the superior performance of TS-MO-derived controllers in mitigating structural responses.



(a) Optimal Pareto fronts (a) Controllers A_1~A_3 (b) Controllers B_1~B_3

Fig. 2 Comparison of structural responses obtained by two approaches



(a) TS-MO (b) DDO-GK-MO

Fig. 3 Optimization results regarding damper distribution obtained by two approaches

To further enhance structural seismic performance, the placement of MR dampers is optimized. Using the six selected FLCs, a multi-objective design optimization based on NSGA-II is conducted to determine the optimal damper distribution. Two soft constraints are incorporated to limit the number of dampers per floor ($N_{MR,i} \leq 3$) and the total number across all floors ($N_{MR} \leq 10$), considering size constraints and economic feasibility. The resulting optimal Pareto fronts for Controllers A_1–A_3 and B_1–B_3 are shown in Figs. 3(a) and (b), respectively. For comparison, results under a uniform damper distribution are highlighted with hollow markers. Three key observations emerge from Fig. 3. First, optimizing damper placement further reduces maximum inter-story drift (leftward shift) but requires a higher average control force (upward shift). Second, controllers with lower control forces yield Pareto fronts closer to the origin, indicating better efficiency. Third, most solutions utilize 10 MR dampers, as increased dampers enhance control force. Notably, three TS-MO-derived solutions use fewer than 10 dampers, whereas only one DDO-GK-MO-derived solution employs nine dampers. These four solutions are labeled ①, ②, ③, and ④ in Fig. 3.

Comparative studies demonstrate that the TS-MO method outperforms the DDO-GK-MO method in convergence speed, surrogate model accuracy, and the quality of design solutions. The TS-MO framework offers a practical and efficient approach for addressing multi-objective optimization problems in structural control, particularly in uncertain and dynamic environments.

REFERENCES

[1] Ellingwood B R. Earthquake risk assessment of building structures [J]. Reliability Engineering & System Safety, 2001, 74(3): 251-262.

[2] Yang Q, Gao R, Bai F, et al. Damage to buildings and structures due to recent devastating wind hazards in East Asia [J]. Natural Hazards, 2018, 92: 1321-1353.

[3] Dyke S J, Spencer Jr B F, Sain M K, et al. Modeling and control of magnetorheological dampers for seismic response reduction [J]. Smart materials and structures, 1996, 5(5): 565.

[4] Daouk S, Louf F, Dorival O, et al. Uncertainties in structural dynamics: overview and comparative analysis of methods [J]. Mechanics & Industry, 2015, 16(4): 404.

[5] Valdebenito M A, Schuëller G I. A survey on approaches for reliability-based optimization [J]. Structural and Multidisciplinary Optimization, 2010, 42: 645-663.

[6] Hu W, Cheng S, Yan J, et al. Reliability-based design optimization: a state-of-the-art review of its methodologies, applications, and challenges[J]. Structural and Multidisciplinary Optimization, 2024, 67(9): 168.