

# Muti-objective optimization of tuned liquid column damper design parameters for vibration control under wind load

Jinsheng Wen<sup>1</sup>, Yi Tang<sup>2</sup>, Yalin Yan<sup>3</sup>, Wei Hao<sup>4</sup>

China Academy of Building Research, Beijing, 100013, China

<sup>2</sup>Corresponding author

E-mail: <sup>1</sup>wenjs951224306@gmail.com, <sup>2</sup>tangyi@cabrtech.com, <sup>3</sup>yanyalin@cabrtech.com,

<sup>4</sup>haowei@cabrtech.com

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**Abstract.** Tuned Liquid Column Dampers (TLCDs) are widely used as passive devices for vibration control in structures dominated by wind loads, utilizing the oscillation of liquid in a U-shaped container to dissipate energy. The effectiveness of TLCDs is significantly influenced by key design parameters, like mass ratio, tuning frequency ratio, and head loss coefficient. This study developed governing equations of TLCDs and investigated the influence of external load excitation spectrum on the vibration mitigation performance. A multi-objective optimization approach based on the Non-dominated Sorting Genetic Algorithm II (NSGA-II) was proposed to identify optimal design parameters of TLCDs under various loading conditions. The results revealed that the external excitation spectrum played a crucial role in determining the optimal parameters, and the damper performance was distinctly different when the excitation frequencies changed. This optimization method was validated through a 200-meter high tower, where the optimized TLCD significantly enhanced vibration control performance at a wide range of wind directions. These findings offered valuable insights for the application of TLCDs in complex environments with varying external load characteristics.

**Keywords:** tuned liquid column damper, wind-induced vibration control, non-dominated sorting genetic algorithm II, optimization parameters.

## 1. Introduction

In recent years, advancements in engineering construction technology, coupled with the pursuit of higher urban space utilization efficiency, have enabled the realization of numerous high-rise structures. For such structures, vibration control measures are essential to mitigate wind-induced vibrations and enhance the comfort of living and working environments. Among these measures, the tuned liquid column damper (TLCD) has emerged as an effective solution owing to its simplicity in design, ease of installation, and low maintenance cost. Since the pioneering work of Sakai [1] et al., who first utilized TLCDs for vibration control in building structures, extensive researches have validated the effectiveness of TLCDs in mitigating wind-induced vibrations [2, 3]. Despite these advancements, the performance of TLCDs remains highly dependent on their design parameters, such as mass ratio, tuning frequency ratio, and head loss coefficient. Improper parameter selection can result in suboptimal vibration mitigation or even adverse effects on the structural response. To enable the practical application of TLCDs in engineering, significant efforts have been devoted to determining their optimal design parameters.

However, conventional methods that optimize TLCD parameters for a single condition are often insufficient for addressing the complex and variable excitation scenarios encountered in practical engineering projects. Researches indicated that TLCD design must account for responses under multiple loading scenarios, which often involve conflicting objectives [4]. Notably, the Non-dominated Sorting Genetic Algorithm II (NSGA-II) [5, 6] has demonstrated superior

performance in solving multi-objective optimization problems and has been widely adopted in engineering applications. This capability allows designers to visualize the trade-offs between conflicting objectives, facilitating more informed decision-making in the engineering design process. This study aims to develop a multi-objective optimization framework for the design of TLCDs under multi-directional and multi-condition wind excitations. The paper introduced a sophisticated multi-objective optimization method using the Non-dominated Sorting Genetic Algorithm II (NSGA-II), specifically tailored for optimizing TLCD (Tuned Liquid Column Dampers) parameters under diverse and dynamic wind load conditions.

## 2. Structure-TLCD analytical model

The tuned liquid column damper (TLCD) is modeled as a U-shaped container with uniform cross-sections. Under external excitations, its dynamic behavior is governed by the following assumptions: (1) The fluid within the TLCD is incompressible; (2) Non-uniform sloshing of the liquid is neglected; (3) The vertical width of the TLCD column is significantly smaller than the horizontal tube length. The schematic diagram of TLCD is shown in Fig. 1.

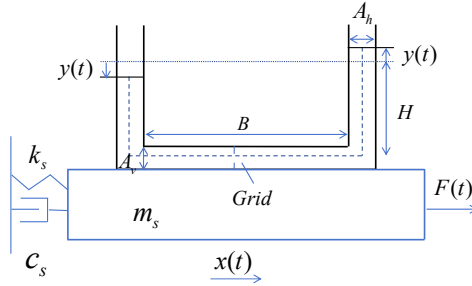


Fig. 1. Schematic diagram of the TLCD system

Based on these assumptions, the equations of motion for a single-degree-of-freedom (SDOF) structure equipped with a TLCD can be derived using Lagrange's equations. The governing equations for the structure and the TLCD liquid column are respectively expressed as:

$$\begin{bmatrix} 1 + \mu & \alpha\mu \\ \mu & 1 \end{bmatrix} \begin{bmatrix} \ddot{x} \\ \ddot{y} \end{bmatrix} + \begin{bmatrix} 2\omega_s\xi_s & 0 \\ 0 & 2\omega_d\xi_d \end{bmatrix} \begin{bmatrix} \dot{x} \\ \dot{y} \end{bmatrix} + \begin{bmatrix} \omega_s^2 & 0 \\ 0 & \omega_d^2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} f(t) \\ 0 \end{bmatrix}, \quad (1)$$

$$\mu = \frac{m_d}{m_s} \quad (2)$$

$$m_d = \rho A_h (2H + B), \quad (3)$$

$$\alpha = \frac{B}{L_e}, \quad (4)$$

where  $\mu$  and  $m_d$  denotes mass ratio and liquid column mass respectively,  $\xi_s$  and  $\xi_d$  denote damping ratio of structures and liquid respectively,  $\alpha$  respond to the ratio between horizontal length and effective length, and  $f(t)$  is the external excitation vector. Allowing the calculation of the structure's RMS displacement, acceleration, and the TLCD liquid velocity as:

$$\sigma_{x,TLCD} = \sqrt{\int_{-\alpha}^{+\alpha} |H_{x,TLCD}(i\omega)|^2 S_f(\omega) d\omega}, \quad (5)$$

$$\sigma_{\dot{x},TLCD} = \sqrt{\int_{-\alpha}^{+\alpha} \omega_s^4 |H_{x,TLCD}(i\omega)|^2 S_f(\omega) d\omega}, \quad (6)$$

$$\sigma_{\dot{y},TLCD} = \sqrt{\int_{-\alpha}^{+\alpha} \omega_s^2 |H_{y,TLCD}(i\omega)|^2 S_f(\omega) d\omega}, \quad (7)$$

where  $|H(i\omega)|$  is the admittance function of water tank and structures,  $\sigma_{\dot{y},TLCD}$  is the root-mean-square (RMS) velocity of the liquid column,  $\sigma_{x,TLCD}$  and  $\sigma_{\ddot{x},TLCD}$  represent the structural RMS displacement and RMS acceleration respectively.

### 3. Multi-objective optimization based on NSGA-II algorithm

The combined influence of the TLCD design parameters highlights their complex interdependence. For structures subjected to varied loading conditions, the vibration mitigation performance varies significantly. Typically, the mass ratio is determined based on site constraints, followed by optimizing the tuning frequency ratio and head loss coefficient for specific vibration mitigation goals.

The TLCD's efficiency is quantified using the vibration mitigation function:

$$\Psi(\lambda, \delta) = \frac{\sigma_{\ddot{x},TLCD}}{\sigma_{\ddot{x}}} \times 100 \%, \quad (8)$$

where  $\sigma_{\ddot{x}}$  and  $\sigma_{\ddot{x},TLCD}$  are the root-mean-square values of the structural acceleration under uncontrolled and controlled conditions, respectively. A lower value indicates better performance.

The optimal tuning frequency ratio  $\lambda_{opt}$  and head loss coefficient  $\delta_{opt}$  are determined by solving:

$$\frac{\partial \Psi}{\partial \lambda} = 0, \quad \frac{\partial \Psi}{\partial \delta} = 0, \quad (9)$$

which identifies the point of maximum mitigation efficiency on the parameter surface. For practical scenarios involving damping and random wind loads, numerical methods are employed to calculate these parameters.

However, the excitation spectra under different wind directions often vary due to environmental disturbances, leading to conflicting mitigation requirements. A single set of TLCD parameters may fail to achieve optimal performance across all scenarios. To address this, an improved NSGA-II genetic algorithm is introduced for multi-objective optimization of TLCD parameters.

The NSGA-II algorithm views each TLCD parameter set as an individual, with its vibration mitigation performance across scenarios forming the fitness value. The fitness value is defined as:

$$fit_n = \frac{1}{n} \sum_{i=1}^n \Psi_m(\lambda_n, \delta_n) - \eta \Lambda(\lambda_n, \delta_n), \quad (10)$$

where  $n$  is the number of individuals,  $m$  is the number of scenarios,  $\Psi_m(\lambda_n, \delta_n)$  is the mitigation efficiency of the  $n$ -th individual under the  $m$ -th scenario,  $\Lambda(\lambda_n, \delta_n)$  is the variance across scenarios, and  $\eta$  is a weighting factor. This formulation balances the global mitigation performance and scenario-specific deviations.

The optimization problem is expressed as:

$$\begin{aligned} & \min fit_n, \\ & \text{subject to } \lambda_{\min} \leq \lambda \leq \lambda_{\max}, \quad \delta_{\min} \leq \delta \leq \delta_{\max}, \quad \Psi_m(\lambda_n, \delta_n) \leq \Psi_g, \end{aligned} \quad (11)$$

where the  $\Psi_g$  denotes target mitigation efficiency.

Steps of the NSGA-II Algorithm:

1. Population Initialization: Randomly generate  $n$  individuals within the parameter constraints. Compute the mitigation efficiency  $\Psi(\lambda_n, \delta_n)$  for each scenario and determine the initial fitness values.
2. Parent Selection: Select elite individuals based on fitness values, using a crossover probability to ensure diversity.
3. Crossover and Mutation: Perform simulated binary crossover to generate offspring, and apply mutation to introduce randomness in certain genes.
4. Iteration and Convergence: Merge offspring with the parent population, calculate new fitness values, and repeat the process until convergence.

By iteratively balancing multiple objectives, NSGA-II identifies a globally optimal parameter set satisfying all constraints.

#### 4. TLCD parameter optimization analysis

This study considers a practical engineering project, where TLCD devices are employed for wind-induced vibration control of a 200-meter-high building. The building is situated in a Class B terrain, with a first-order natural frequency of  $f_s = 0.284$  Hz, a generalized mass of  $m_s = 1.3 \times 10^7$  kg and a structural damping ratio of  $\xi_s = 2\%$ . The Fig. 2 depicts the relative positioning of the main building, surrounded by nearby structures and a tank layout area. The wind direction angles, ranging from  $0^\circ$  to  $360^\circ$ , represent various wind directions tested during the experiment. These angles were chosen to comprehensively evaluate the wind-induced acceleration responses of the structure under different wind orientations.

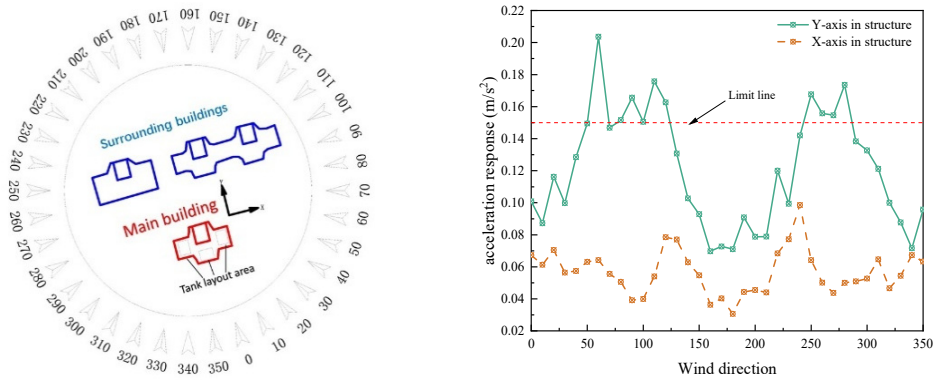


Fig. 2. Acceleration response for various wind directions

Wind-induced acceleration responses across various directions are shown in Fig. 2. According to the technical specification of concrete structures of tall building, the acceleration of residential structures must not exceed a specific threshold  $0.15 \text{ m/s}^2$ . Due to the complex wind environment around the project site, the structure exceeds the acceleration limit in multiple wind directions along the Y-axis. This necessitates an in-depth analysis of TLCD optimization measures for these critical scenarios.

To address conflicting requirements across scenarios, this study employs the NSGA-II algorithm for multi-objective optimization. The optimization process initializes a population of 100 individuals with a crossover probability of 0.5 and a mutation probability of 0.1, iterating for 500 generations. Fig. 3 shows the convergence of the NSGA-II algorithm, demonstrating stable fitness values after 150 iterations.

For validation, a weighted averaging method (WAM) is also employed. The weights are determined based on the relative importance of each scenario, as defined by:

$$W_i = \frac{\sigma_{\ddot{x},i} - \sigma_{\ddot{x},g}}{\sigma_{\ddot{x},\max} - \sigma_{\ddot{x},g}}, \quad (12)$$

where  $\sigma_{\ddot{x},i}$  represents the uncontrolled acceleration RMS for scenario, and  $\sigma_{\ddot{x},\max}$  is the maximum RMS across all scenarios. The optimization objective function is expressed as:

$$G(\psi) = \frac{1}{n} \sum_{i=1}^n W_i \psi_i(\lambda, \delta), \quad (13)$$

where  $\psi_i(\lambda, \delta)$  is the normalized mitigation efficiency for scenario.

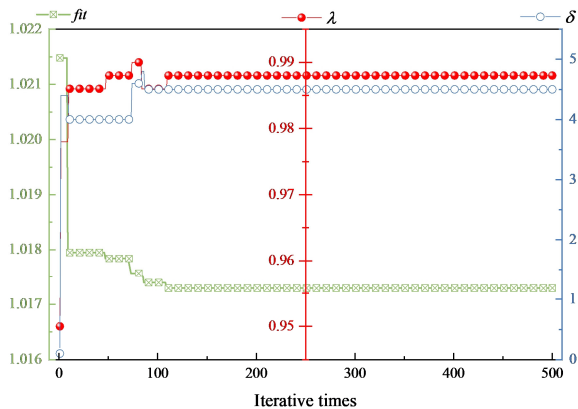


Fig. 3. Stability of fitness and parameter values

Fig. 4 illustrates the objective function distribution for TLCD optimization parameters, and Table 1 summarizes the optimal design parameters obtained using two optimization methods: the weighted averaging method and the NSGA-II algorithm. The results demonstrate that both methods converge to similar parameter values, indicating their reliability and accuracy.

Table 1. TLCD optimization design parameters

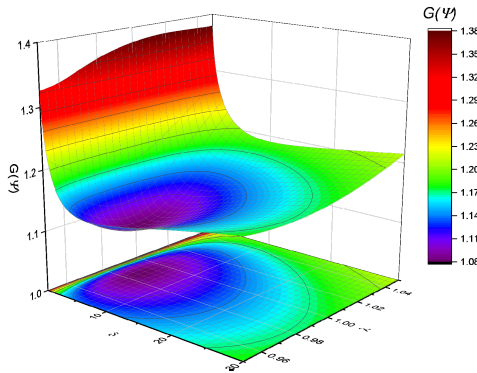
Optimal parameters	WAM	NSGA-II
$\delta_{opt}$	4.6	4.5
$\lambda_{opt}$	0.988	0.988

It is noteworthy that the weighted averaging method requires exhaustive enumeration of all parameter combinations  $(\lambda_n, \delta_n)$  within the constrained design space. This approach becomes computationally expensive as the number of control objectives increases. As shown in Table 2, the NSGA-II algorithm achieves nearly identical optimal design parameters to the weighted averaging method, while requiring fewer computational resources. Specifically, the NSGA-II algorithm identified the globally optimal parameters of  $\lambda_{opt} = 0.988$ ,  $\delta_{opt} = 4.5$  which demonstrates enhanced robustness and computational efficiency.

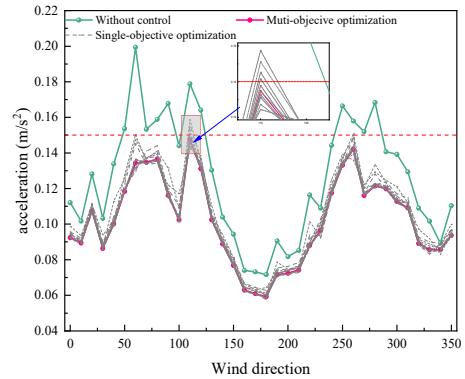
The acceleration distribution curves of the structure under TLCD control for various wind directions are presented in Fig. 5, compared the results of optimized TLCD parameters (red solid line) with scenario-specific parameters (dashed line) and the uncontrolled case (green solid line). The results indicate a significant reduction in peak acceleration values when TLCD devices are implemented, demonstrating their effectiveness in vibration mitigation.

However, discrepancies arise when TLCD parameters optimized for one scenario are applied to others. Due to the variations in wind direction and corresponding excitation spectra, scenario-specific TLCD designs may lead to suboptimal or even adverse performance under other

conditions. This underscores the limitations of single-scenario optimization, as it fails to account for the dynamic variability of multi-directional wind loads.



**Fig. 4.** Objective function distribution of TLCD parameter optimization



**Fig. 5.** Acceleration response using optimized TLCD parameters

## 5. Conclusions

This study focused on addressing the challenges associated with designing tuned liquid column dampers (TLCDs) under varying wind-induced excitations, emphasizing the impact of excitation variability on the optimal TLCD design parameters.

The NSGA-II algorithm was successfully employed to address the challenges of conflicting design requirements under multiple excitation scenarios. By incorporating scenario-specific excitation characteristics into the optimization framework, the algorithm identified globally optimal TLCD parameters that ensured robust vibration mitigation across all conditions. This approach effectively overcame the limitations of single-scenario optimization, which often led to suboptimal performance in varying wind environments.

The findings underscored the importance of tailoring TLCD designs to site-specific wind load conditions, particularly in projects with diverse wind environments. The proposed methodology provided a systematic framework for achieving consistent and reliable vibration mitigation performance, ensuring that TLCD systems are adaptable to practical structural challenges.

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## Data availability

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

## Conflict of interest

The authors declare that they have no conflict of interest.

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