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RC model control subjected to earthquakes using piecewise Lyapunov criterion in ambient intelligence

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Abstract. This paper proposes a composite form of fuzzy modal control plan based on a piecewise Lyapunov criterion in ambient intelligence (AI). In some cases, these goals are of equal importance and cannot be easily prioritized. Environmental intelligence systems are being developed to handle multi-objective problems related to daily activities. This paper proposes a context-aware structure to provide strategies in an AI control system. Based on context data from sensors distributed throughout the environment, the modelled system recognizes the individual state, makes supporting decisions with no designation for control targets, and executes operations that is based on the environment feedbacks. To validate the developed model, an example using the system to deal with a practical engineering structural stability of analysis and control is described. The objectives of this paper are access to adequate, safe and affordable housing and basic services, promotion of inclusive and sustainable urbanization and participation, implementation of sustainable and disaster-resilient buildings, sustainable planning and management of human settlement. Therefore, the goal is believed to be achieved in the near future through the continuous development of AI and control theory for a better life from the environment and built systems.

Keywords: adaptive system; AI; ambient intelligence; fuzzy model and NN; Lyapunov energy function; sustainable and disaster-resilient

1. Introduction

Many researchers have conducted significant theoretical and experimental research in the field of bridge life assessment (Bai *et al*. 2021, Tan *et al*. 2023). Advances in this field include, in particular, the creation of fatigue damage models (Song *et al*. 2022, Xu *et al*. 2022, Tian *et al*. 2024), the study of crack initiation methods and the assessment of the overall fatigue life of the structure (Zhong *et al*. 2022a, b, Xu *et al*. 2025). This design is simple and effective (Huang *et al*. 2021a, b, Lu *et al*. 2017, Bibi *et al*. 2024, Zhou *et al*. 2020a, b, Zhang *et al*. 2023, 2024). Since latency is a concept in a loop, RC has control and learning capabilities (Shi *et al*. 2023, Zhang *et al*. 2023a, b, Li *et al*. 2024). Thus, current orders contain information from the previous period. The error gradually converges as the period repeats. This process behaves like two-dimensional (2D) special elements. Zhang *et al*. (2023c) created a 2D hybrid repetitive control system model and independently controlled control and learning behavior. After the success, researchers adopted a new 2D hybrid model of Modified Repetitive Control System (MRCS). A combination of 2D control gain and maximum cutoff frequency is obtained using an iterative algorithm (Chen *et al*. 2022a, b, c, Huang *et al*. 2022a, b, Du and Wang 2014, Cao *et al*. 2024, Lin *et al*. 2022a, b). As MRCS becomes more common in real systems, a large number of methods offer 2D-space MRCS to significantly improve measurement performance (Wang *et al*. 2024a, b, Sun *et al*. 2024, Long *et al*. 2024, Huang *et al*. 2021a, b, Zhao *et al*. 2020). Moreover, in order to increase a robot's productivity, it must be continuously controlled. Therefore, controlling the position of the operator is necessary (Yao *et al*. 2022, 2024, Xu *et al*. 2022, Wu *et al*. 2023, Wang *et al*. 2023a, b, Zhang 2022a, b)

Environmental Intelligence is an interdisciplinary field designed to increase intelligence for control of the environment, making it usable to the needs of users. Suppose that people are seeking to obtain equipment with two characteristics: efficient and effective.

To handle this type of problem, researchers have proposed multi-objective optimization theory. Multi-objectiveness corresponds to those problems where one has to achieve several goals rather than just one goal, and often, these goals conflict with each other, so it is impossible to find a global optimal solution. In addition to the reproduction of human reasoning, the AmI system may need to be able to hand other complex problems, for example, in a common example, seeking user comfort while optimizing resources. These complex situations require the use of more realistic models to faithfully reproduce the dynamic aspects; linear models are too simplistic and not suitable for this situation. However, while it is clear that there is a need to consider these differing aspects when

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developing more versatile applications, it is difficult for offering such models.

Some have suggested using genetic algorithms for example, multi-objective optimization or particle swarm optimization, to solve multi-objective problems, but ambiguities allow for the inference of multiple input values. In the AI system, multiple sensors capable of capturing contextual data such as shape, motion, temperature and sound recognition can be used. Ideally, a context-aware system should focus on advanced data, however, the sensor can only generate context data, not information. These data lack the semantics that give them meaning. One way to provide semantics for data obtained from sensors is to use a model that identifies the context of interest. By identifying related entities and their relationships, these models can be used to capture the data relevant to the system domain. These systems are known as situational awareness systems. Understanding the entities in the environment and the relationships between them is necessary to enabling the applications to operate and interact in a more beneficial way related to their domains. Situational awareness (SA) is critical to effective decision making because it is able to understand changes in background knowledge.

Some special nonlinear systems are decomposed into a combination of a linear plant and a nonlinearity that is treated as a lumped disturbance. Disturbance-rejection methods are used to handle the nonlinearity. Then, 2D repetitive- control methods of linear systems are directly applied to the compensated nonlinear systems. However, such methods have a trade-off between disturbance rejection and reference tracking. Since the system needs an additional degree of freedom to estimate and compensate for the nonlinearity, the structure and design are complex compared to a linear T-S fuzzy model to approximate nonlinear plants infinitely, it is an effective way to analyze and design nonlinear systems. A significant advantage is that the antecedents are fuzzy membership functions, and the consequents are crisp linear subsystems. Therefore, linear control theory is directly applied to control and synthesize nonlinear systems. Many excellent design methods have been proposed for the FLC system and a number of efficient methods are recommended to address durability, stability and time delay. Intelligent control technology, such as the adaptive method and the adaptive dynamic programming method, is believed to be an optimal tool in analyzing the nonlinear systems. Intelligent control technology can be very useful in solving control problems in motion control of drones. Examining the existing literature, the researchers found that intelligent control is particularly attractive to a class of highly coupled non-linear insecure systems because of their attractive special properties, such as those not suitable for systems that work well. In a mathematical form based on the experience of human experts, this heuristic method is simple and easy to implement. Intelligent control methods usually include neural network fuzzy logic (FL) (Tan *et al*. 2023, Tian *et al*. 2024), genetic algorithm (GA) (Xu and Li 2025, Lu *et al*. 2017) and adaptive repetitive neuro-fuzzy control technology (Zhou *et al*. 2020a, b, Zhang *et al*. 2023, Li *et al*. 2024). It has stronger resistance to uncertainty about fluid dynamics and excellent anti-interference ability. The known shortcomings of intelligent control are listed below: Conventional obscure control requires specialized knowledge or huge computing time only for the required performance. In neural network (NN) control, the approximation of time lag makes the theory not applicable. It was later widely used in various fields of modern science such as fluid mechanics, optics, quantum mechanics, and nonlinear control theory. In recent years, the nonlinear control has great breakthrough not only by control theory but also the exploitation of fuzzy models.

Based on the disturbance-rejection methods or T-S fuzzy model, many works transformed the nonlinear repetitive control into linear matrix inequality (LMI)-constrained parameter optimization by constructing the tuning parameters. The mean-square error is usually chosen as a cost function during the single-objective optimization process. Zhang *et al*. (2021a, b) used the PSO algorithm and a single cost function that mixed control and learning performance to optimize the best 2D control gains. However, the cost function considers the overall performance of control and learning. The mixed evaluation leads to the attention to control convergence and the neglect of learning efficiency, optimizing a large control gain to meet the desired performance requirements. On the other hand, the cost of a large control gain is expensive in control engineering practice. A large control gain deteriorates the system performance, such as amplifying the impact of high-frequency noise on the system output and enabling the system to be unstable. Therefore, how to separately evaluate control and learning performance and then simultaneously optimize them are the motivations of this paper.

This study is organized as follows. First, a description of the system is presented. Then, based on the Lyapunov method, a stability criterion is derived to ensure asymptotic stability. Finally, a numerical example is given to demonstrate the results, and then conclusions are drawn to validate other control methods to be used. In addition, comparisons with numerical results are made to demonstrate its control performance.

2. Preliminary problem

A generalization of the Fuzzy concept was resented in Eq. (1).

$$C = L^{in\times};\quad R;\quad L^{out} \tag{1}$$

A *constant* is represented as follows (Eq. (2)).

$$C \in C \tag{2}$$

To eliminate the influence of modeling error and exogenous disturbance on control performance to a minimum level, a robustness design of fuzzy control via NN-based approach is proposed in this paper. A multilayer perceptron NN of which the transfer functions are of the sigmoid class symmetric to the origin is first established to approximate a nonlinear plant. Then, the dynamics of the

NN model is converted into an LDI representation. Consider an NN model, has S layers with $R^q(q = 1, 2, \cdots, S)$ neurons for each layer, in which $x(k) \sim x(k - m + 1)$ are the state variables and $u(k) \sim u(k - n + 1)$ are the input variables. An LDI (linear difference inclusion) system in the state-space representation is introduced and it can be described as $\boldsymbol{x}(k+1) = \sum_{i=1}^{\varphi} h_i(k)\boldsymbol{J}_i\boldsymbol{Z}(k)$. Suppose that there exists a bounding matrix $\Delta\boldsymbol{H}_{ij}$ such that

$$\boldsymbol{e}^T(k)\boldsymbol{e}(k) \leq \{\boldsymbol{H}_q\boldsymbol{x}(k)\}^T\{\boldsymbol{H}_q\boldsymbol{x}(k)\} \tag{3}$$

between the closed-loop nonlinear system and the closed-loop NN system. Given a real number $\gamma > 0$, it is said that the exogenous input is locally attenuated by γ if there exists a neighborhood U of $\boldsymbol{x}(k) = 0$ such that for every positive integer N and for every $\boldsymbol{b}(k) \in \ell_2([0, N], \Re^r)$ for which the state trajectory of the closed-loop nonlinear system starting from $\boldsymbol{x}(0) = 0$ remains in U for all $k \in [0, N]$, the response $\boldsymbol{x}(k) \in \ell_2([0, N], \Re^m)$ satisfies

$$\sum_{k=0}^{N} \boldsymbol{x}(k)^T\boldsymbol{Q}\boldsymbol{x}(k) \leq \gamma^2 \sum_{k=0}^{N} \boldsymbol{b}(k)^T\boldsymbol{b}(k). \tag{4}$$

In other works, fuzzy logic is associated with the decision after the situation is detected. There has been a great deal of work seeking to address to be defined according to a standard.

We did not find any similar studies in the literature addressing all the aspects involved in this study (background and situational awareness, multi-objective decision making and TS type theory). In short, this research complements past efforts by adding new modules to facilitate reasoning and further the development of environmentally intelligent automated systems.

First, it must be identified the problem P for which the application will be developed, that is, it must be defined what multiobjective problem this application has to manipulate.

$$obj : (name, \{v\}) \tag{5}$$

$$P : \{ obj\_1, obj\_2, \cdots, obj\_n \} \tag{6}$$

The above definition must be performed for each target defined for the application. The situation can be characterized at the perceived level of the SA, since from this situation, action is needed to change something in the environment. In a multi-objective problem, there are few moments when the input value can be considered sufficient. Since the goals of the application may be different, the situation of interest can be detected by a different set of events. It may present an "end" that is identified by a new event. Typically, this event is expected (but not guaranteed) to occur after performing the automatic actions defined later in this model.

$$Si : (name, evSet, F\,e) \tag{7}$$

$$evSet : \{ev1, ev2, ..., evn\} \tag{8}$$

For the system matrices T, Q, U, and W the individual matrices have their corresponding dimensions, and a scalar ξ, if the following inequality

$$\mathrm{T} + \mathrm{W}^{\mathrm{T}}\mathrm{Q}^{\mathrm{T}} + \mathrm{QW} < 0 \tag{9}$$

is established, it means that the following formula is also established

$$\begin{bmatrix} \mathrm{T} & \star \\ \xi\mathrm{Q}^{\mathrm{T}} + \mathrm{UW} & -\xi\mathrm{U} - \xi\mathrm{U}^{\mathrm{T}} \end{bmatrix} < 0. \tag{10}$$

The general nonlinear system is transformed into linear subsystems via the T-S fuzzy model.

$$\begin{cases} \dot{x}_p(t) = A(\Lambda)x_p(t) + B(\Lambda)u(t) \\ y(t) = C(\Lambda)x_p(t) \end{cases} \tag{11}$$

where $x_p(t) \in \mathbb{R}_n$ represents the state variable; $u(t) \in \mathbb{R}_p$ represents the control input variable; and $y(t) \in \mathbb{R}_q$ repressents output variable.

$$\begin{cases} A(\Lambda) = \sum_{i=1}^{r} \Pi_i(\Lambda(t))A_i, B(\Lambda) = \sum_{i=1}^{r} \Pi_i(\Lambda(t))B_i \\ C(\Lambda) = \sum_{i=1}^{r} \Pi_i(\Lambda(t))C_i \end{cases} \tag{12}$$

A_i, B_i, and C_i represent the matrices of linear subsystems; r represents the number of fuzzy rules; $\Lambda(t) = [\Lambda_1(t), \Lambda_2(t), \cdots, \Lambda_\iota(t)]$, $v_i(\Lambda(t)) = \Pi_{m=1}^{\iota} M_{im}(\Lambda_m(t))$, $\Pi_i(\Lambda(t)) = v_i(\Lambda(t))/\sum_{i=1}^{r} v_i(\Lambda(t))$, $M_{im}(\Lambda(t))$ represents the degree of a membership $\Lambda_m(t)$ in M_{im}; and $M_{im}(m = 1,2, \dots, \iota)$ represents fuzzy sets. We have $\sum_{i=1}^{r} \Pi_i(\Lambda(t)) = 1, 0 \leq \Pi_i(\Lambda(t)) \leq 1$, for all t and $i = 1,2, \dots, r$.

Therefore, the T-S machine learning fuzzy model, representing the structural system, can be represented as follows

Rule i: IF $x_1(t)$ *is* M_{i1} *and* $\cdots$ *and* $x_p(t)$ *is* M_{ip}

THEN, $\dot{x}_j(t) = A_{ij}x_j(t) + \sum_{k=1}^{N_j} A_{ikj}x_j(t - \tau_{kj}) + B_{ij}u_j(t)$

where $i = 1,2, \cdots, r$ and r is the rule number; $X(t)$ is the state vector; $M_{ip}.(p = 1,2, \cdots, g)$ are the machine learning fuzzy sets and $x_1(t) \sim x_p(t)$ are the premise variables.

A neural fuzzy system can be defined as LMI and LDI form (see Tian *et al.* (2024)) as follows (Tan *et al.* 2023)

$$\dot{Y}(t) = A(a(t))Y(t), . A(a(t)) = \sum_{i=1}^{r} h_i(a(t))\overline{A}_i$$

For the convenience of control design, the MRC (in Fig. 1) is composed of a common MRC in parallel with a repetitive controller with a constant $w \in [0,1)$. The contstant w is used as a tuning parameter to relax the system design. $q(s) = 1/(T_c s + 1)$ is the LPF. ω_c.

The MRC is expressed as

$$\begin{cases} \dot{x}_f(t) = -\omega_c x_f(t) + \omega_c x_f(t-T) \\ \qquad +\omega_c e(t) + \dot{e}(t) \\ x_d(t) = w x_d(t-T) + e(t) \end{cases} \tag{13}$$

where $e(t) = r(t) - y(t)$; $x_f(t)$ and $x_d(t)$ are the state variables; and T is the delay determined by the periodic signal.

According to the parallel distribution compensation scheme, we construct the fuzzy control law with corresponding r fuzzy rules. Then, the overall control law is

$$u(t) = K_p(\Lambda)x_p(t) + K_f(\Lambda)x_f(t) + K_d(\Lambda)x_d(t) \tag{14}$$

If there exists a positive definite symmetric polynomial matrix $P(x) \in R^{n\times n}$, the control gain $K_i(y) \in R^{m\times q}$ and a scalar $\gamma > 0$ satisfy the following inequalities

$$\begin{aligned} & P(x) > 0 \\ & \chi_{iii}(x,y) < 0, \quad i = 1, \dots, r \\ & \chi_{iij}(x,y) + \chi_{iji}(x,y) + \chi_{jii}(x,y) < 0, \quad i < j \le r \\ & \chi_{ijj}(x,y) + \chi_{jij}(x,y) + \chi_{jji}(x,y) < 0, \quad i < j \le r \\ & \chi_{ijk}(x,y) + \chi_{ikj}(x,y) + \chi_{jik}(x,y) + \chi_{jki}(x,y) \\ & \quad +\chi_{kij}(x,y) + \chi_{kji}(x,y) < 0 \quad i < j < k \le r \end{aligned}$$

where $i < j < k \le r$

$$\chi_{ijk} = \begin{bmatrix} -G^T(x) - G(x) + P(x) & \star & \star & \star \\ 0 & -\gamma^2 I & \star & \star \\ \bar{A}_{ijk}(x,y)G(x) & B_{\infty i}(x) & -P(x^+) & \star \\ \bar{C}_{ijk}(x,y)G(x) & D_{\infty i}(x) & 0 & -I \end{bmatrix}$$

For the comprehensive analysis of the static output feedback controller, we use Lyapunov's theorem to analyze its stability, where the Lyapunov function V(x) is expressed as the following form

$$V(x) = x^T(t)P^{-1}(x)x(t) \tag{15}$$

Now $0 > \Delta V(x) - \gamma^2\omega^T\omega + z^T z$, where $\Delta V(x) = V(x(t+1)) - V(x(t))$, while $V(x(t+1)) = x^T(t+1)P^{-1}(x^+)x(t+1)$, x^+ means $x(t+1)$, then

$$\begin{aligned} & 0 > \Delta V(x) - \gamma^2\omega^T\omega + z^T z \\ & = x^T(t+1)P^{-1}(x^+)x(t+1) - x^T(t)P^{-1}(x)x(t) \\ & - \gamma^2\omega^T\omega + z^T z \\ & = \begin{bmatrix} x \\ \omega \end{bmatrix}^T \begin{bmatrix} \bar{A}_{\mu\mu\mu}^{(x,y)T} P^{-1}(x^+) \star - P^{-1}(x) + \bar{C}_{\mu\mu\mu}^T(x,y)\bar{C}_{\mu\mu\mu}(x,y) \\ B_{\infty\mu}^T(x)P^{-1}(x^+)\bar{A}_{\mu\mu\mu}(x,y) + D_{\infty\mu}^T(x)\bar{C}_{\mu\mu\mu}(x,y) \end{bmatrix} \end{aligned}$$

$$\begin{bmatrix} A_{\mu\mu\mu}^T(x,y)P^{-1}(x^+)B_{\infty\mu}(x) + \bar{C}_{\mu\mu\mu}^T(x,y)D_{\infty\mu}(x) \\ B_{\infty\mu}^T(x)P^{-1}(x^+)B_{\infty\mu}(x) + D_{\infty\mu}^T(x)D_{\infty\mu}(x) - \gamma^2 I \end{bmatrix} \begin{bmatrix} x \\ \omega \end{bmatrix}$$

which $\bar{A}_{\mu\mu\mu}^T(x,y)P^{-1}(x^+)\star$ means $\bar{A}_{\mu\mu\mu}^T(x,y)P^{-1}(x^+)$ $\bar{A}_{\mu\mu\mu}(x,y)$.

When $x \in R^r$, a polynomial function f(x) is the sum of squares, it can be expressed as

$$f(x) = \sum_{i=1}^{r} g_i^2(x) \tag{16}$$

where $g_1(x)\cdots g_t(x)$, $g_2(x)$ is a polynomial function, and a convex polyhedral cone K^d constitutes a polynomial $P^d(x)$, and $P^d(x)$ conforms to Definition 1, and can be decomposed into a sum of squares, then for all d, $K^d \subseteq K^{d+1}$

$$P^{d+1}(x) = \left(\sum_{k=1}^{t} x_k^2\right) P^d(x) = \sum_{k=1}^{t}\sum_{i=1}^{r}(g_i x_k)^2. \tag{17}$$

Define a monomial $X = x_1^{\alpha_1}x_2^{\alpha_2}\cdots x_r^{\alpha_r}$ to the power of α, where $x \in R^r$all α_i are non-negative integers, i = 1, 2, ⋯, r and satisfy $\alpha = \alpha_1 + \alpha_2 + \cdots + \alpha_r$.

f(x) is a polynomial function of power 2d, $x \in R^r$ and it $Z(x) \in R^p$ is a vector of all monomial combinations of x whose power is not greater than d, then f(x) conforms to definition 1, if and only if there are half positive. The constant matrix $Q \in S^p$ satisfies the following equation

$$f(x) = Z^T(x)QZ(x) \tag{18}$$

The meaning of the above formula is: the square sum polynomial function of the 2d power can always be decomposed into a monomial structure of the d power.

Suppose it $F(x) \in S^N$ is a polynomial matrix of power 2d, $x \in R^r$, and Z(x) is a vector composed of all monomials of $v \in R^N x$ whose power is not greater than d, and the following theorem is derived

(1) $F(x) \ge 0$ All exist

$$x \in R^r. \tag{19}$$

(2) If it $v^T F(x) v$ is a sum of squares structure

$$F(x) \ge 0 \text{ where } v \in R^N. \tag{20}$$

(3) $v^T F(x) v$ is a sum of squares structure, if and only if there is a half positive definite constant matrix Q that satisfies

$$v^T F(x) v = (v \otimes Z(x))^T Q (v \otimes Z(x))$$

where ⊗ is the Kronecker product.

The sufficient and necessary condition relations of the above theorems, (1)⇐(2) and (2)⇔(3), are explained here as follows

(1)⇐(2): $v^T F(x) v$ When it is the sum of squares, it means that $v^T F(x) v \ge 0F$ (x) ≥ 0 is known from linear algebra.

(2)⇒(3): $v^T F(x) v$ When it is the sum of squares, it can be seen from definition 3 that Z (x) is changed to x, and the

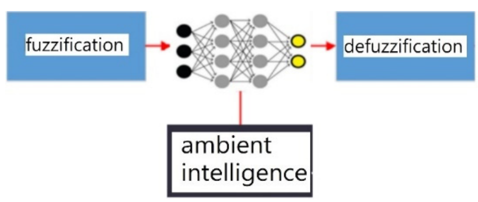

Fig. 1 Framework of the modified fuzzy controller

vector composed of all monomials of v is v ⊗ Z (x), so the proof is obtained.

(i) find

$$\varepsilon_1^* = \frac{r - r_s}{(r - r_s)(\sum_{i=0}^{n} \| \tilde{A}_{2i} \|) + \sum_{i=0}^{n} (\sum_{j=0}^{n} \| \tilde{A}_{1j} \|) \| A_{2i} \| (r - |\alpha|)^{-i}}; \quad (26)$$

(2)⇐(3): we know $(v \otimes Z(x))^T Q (v \otimes Z(x))$ sum of squares $(v \otimes Z(x))^T Q (v \otimes Z(x)) = v^T (I \otimes Z(x))^T Q (I \otimes Z(x)) v = v^T F(x) v$.

F(x) in definition 4 is the sum of squares matrix (SOS matrix), where the internal elements of the v vector must be independent of x to ensure that the matrix $v^T F(x) v$ value x satisfies the definition of the sum of squares, and the v vector on both sides of F(x) is used to $v^T F(x) v$ convert the equation into a scalar form, so that SOSTOOLS can solve it. In addition, the vectors hanging on both sides of F (x) can also be $\hat{x}$, and its usage depends on the simulation topic. If the system matrix is a constant matrix, use $\hat{x}^T F(x) \hat{x}$ form; when the system matrix is a polynomial matrix, use $v^T F(x) v$ form.

According to (18), the fast subsystem of original plant can be obtained in the following form

$$x_f(k+1) = \varepsilon \sum_{i=0}^{n} \tilde{A}_{2i} x_f(k-i). \quad (21)$$

This paper focus on the interests understanding the stability coupled connections for subsystems with respect to practical nonlinearities. The following theoretical consequence could be derived by the proposed proof.

Theorem 2: If the slow and fast subsystems are both $D(\alpha, r)$ -stable, then the original system is also $D(\alpha, r)$ -stable for a sufficiently small ε.

Proof of Theorem 2:

Rewrite the original system as

$$X_1(k+1) = M_1 X_1(k) + M_2 X_2(k) \quad (22)$$

$$X_2(k+1) = M_3 X_1(k) + M_4 X_2(k), \quad (23)$$

Remark 1 (Zhou *et al.* 2020b): Basically, two terms can be used to test the asymptotic stability of ***N*** multi-delay large nonlinear systems. So, it makes sense to test for asymptotic stability under these two conditions, and return the other condition if it fails.

3. Searching bound ε^*

The purpose of algorithm is given prior by the assumption 3.1.

Assumption 3.1: Assume (24-25) are given

$$r_o \equiv \left\| \begin{bmatrix} A_{10} & 0 \\ A_{20} & 0 \end{bmatrix} - \alpha I \right\| + \sum_{i=1}^{n} (r - |\alpha|)^{-i} \left\| \begin{bmatrix} A_{1i} & 0 \\ A_{2i} & 0 \end{bmatrix} \right\| < r \quad (24)$$

$$r_s \equiv \|A_{10} - \alpha I\| + \sum_{i=1}^{n} (r - |\alpha|)^{-i} \|A_{1i}\| < r \quad (25)$$

In other words, the systems with $\varepsilon = 0$ are $D(\alpha, r)$ -stable.

Theorem 3. In the condition, $D(\alpha, r)$ -stability (with $r > |\alpha|$), then (19) for all $\varepsilon \in (0, \varepsilon^*)$ where ε^* are decided based on the obvious 3 conditions

(ii) find

$$\varepsilon_2^* = \frac{1}{\sum_{i=1}^{n} \|\tilde{A}_{2i}\| (r - |\alpha|)^{-(i+1)}}; \quad (27)$$

(iii) find

$$\varepsilon_3^* = \frac{r - r_o}{\sum_{i=0}^{n} \left\| \begin{bmatrix} 0 & \tilde{A}_{1i} \\ 0 & \tilde{A}_{2i} \end{bmatrix} \right\| (r - |\alpha|)^{-i}}; \quad (28)$$

(iv) choose $\varepsilon^* = min(\varepsilon_1^*, \varepsilon_2^*, \varepsilon_3^*)$... (29)

4. Examples

A system based on a benchmark question is discussed (see Zhou *et al.* 2022a). Since the system order n' is actually unknown when applying actual measured cases, system modal parameters must be extracted for different values; a diagram identifying n' the relationship between modal parameters and system order is drawn n', which is called a Stabilization Diagram. This removes the unstable modal parameters and obtains the location of the true mode of the system. The method of drawing a steady-state diagram is to select the pole of one system order (Pole) and compare it with the pole of the next system order, and define the criterion (Criteria) as the difference between the two, including modal frequency and modal damping ratio. If the second-order pole satisfies the restriction range of the difference between the modal vibration shape and the modal vibration shape, the pole is calibrated as a stable point (Stable Pole). Accordingly, spurious numerical extremes will be left alone or filtered out due to instability. The modal frequency and damping ratio set in this article The stability conditions of the vibration shape are

$$\frac{\omega_i'' - \omega_i^{\kappa+2}}{\omega_i^{n^*}} < 1\% \quad (30)$$

$$\frac{\xi_i^{n'} - \xi_i^{n'+2}}{\xi_i^{n'}} < 3\% \quad (31)$$

$$1 - MAC(n', n'+2) < 1\% \quad (32)$$

Among them, n' is the state number, which is the system order; i is the modal order (i = 1, 2, 3…). The parameter MAC (Modal Assurance Criterion) of the third term inequality is defined as follows

$$\text{MAC}\ (n', n'+2) = \frac{|\phi_i^{n^T} \cdot \phi_i^{n^*+2}|}{|\phi_i^{n'^T} \cdot \phi_i^{n'}| |\phi_i^{n^{**2^T}} \cdot \phi_i^{n^{n+2}}|} \quad (33)$$

MAC value is between 0 and 1. It is a judgment parameter for estimating the relationship between two vibration shapes. Just like the generalized cosine of the angle between two vectors, the more consistent the directions of the two vectors, the closer the cosine value is to 1. That is, the correlation between the two is high. When the two groups of vibration shapes have no correlation, the MAC is 0. Therefore, MAC can be used to determine the stability of modal vibration shapes.

In summary, from the aforementioned state space methods, we know that the poles (Poles) implicit in the state matrix (A matrix) are the key to solving the system modal parameters, and the poles do not completely represent the real mode, including the influence of noise. Produced false extremes. According to the steady state diagram method, $n' \times n'$ the modal frequency, modal damping ratio and modal damping ratio of the representative system can be obtained by comparing the poles of the $(n'+2) \times (n'+2)$ order A matrix and the poles of the order A matrix using the discrimination criteria of Eq. (32) to Eq. (33). vibration shape.

According to the NBC1990 specification for the load recommendations for man-made activities in multi-functional venues, the frequency of man-made activities is between 1.5 Hz and 8.25 Hz. Therefore, the number of modes selected in this article is "the number of modes that can be excited by external forces", which is the first three modes. state. Considering that the external force is uncertain, frequency culverts are used to control multiple modes. Therefore, the placement method of MTMD is "comprehensive type". This type can control all modes excited by external forces. The TMD is placed near the midpoint of the floor to control the first mode. state, two The TMD is placed at the maximum position of the second mode response to control the second mode. Although there are three positions where the third mode frequency response is larger, the midpoint of the floor mainly uses the MTMD to control the first mode, so the third mode will be controlled here. The MTMD of the three modes is set to two. Consider not using it TMD causes a burden on the floor installation. It is set to control the average modal mass ratio of each TMD in the second mode to 0.1%, that is, the total modal mass ratio is 0.2%. The average value of each TMD in the third mode is controlled. Designed with a modal mass ratio of 0.1%, that is, the total modal mass ratio is 0.2%. Since controlling the MTMD of the first mode is more important, each TMD is designed with a modal mass ratio of 0.2%, that is, the total mode The mass ratio is 1%.

Then according to Eq. (32), the MTMD optimization parameters that control each mode can be designed. The results after the comprehensive MTMD design are shown in Tables 1 to 3. The modal acceleration transfer functions before and after the comprehensive MTMD is installed on the floor are shown in Figs. 2 to 4. After the comprehensive MTMD is installed, the first mode The equivalent damping ratio of the first mode increased from 2.8% to 5.45%; the equivalent damping ratio of the second mode increased from 3.5% to 5.13%; the equivalent damping ratio of the third mode increased from 3.0% to 6.04%.

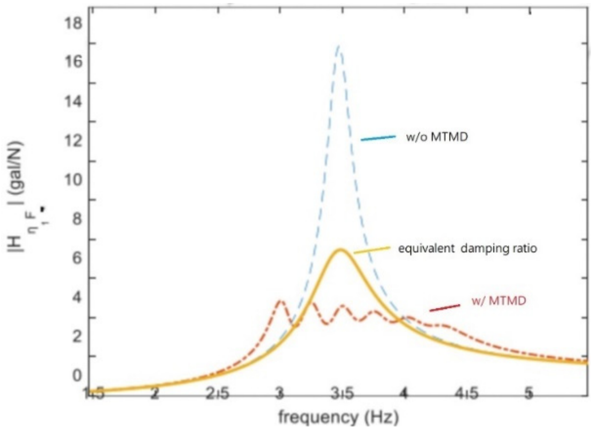

Fig. 2 The first mode acceleration transfer function of comprehensive MTMD installed on the third floor floor slab

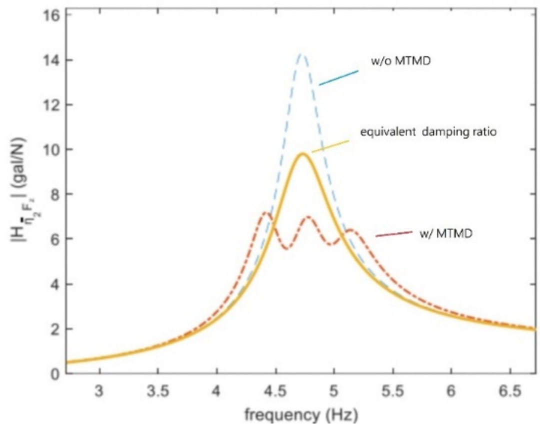

Fig. 3 The second mode acceleration transfer function of comprehensive MTMD installed on the third floor floor slab

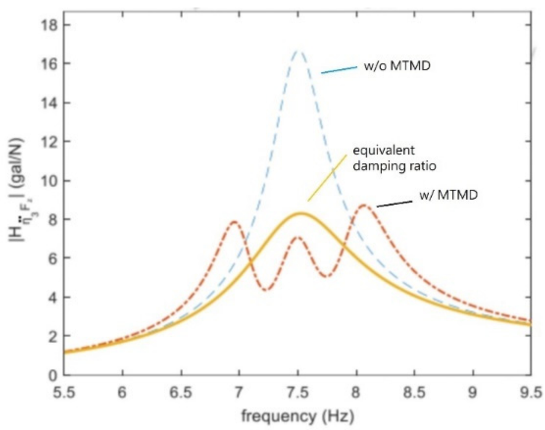

Fig. 4 The third mode acceleration transfer function of comprehensive MTMD installed on the third floor floor slab

Table 1 Design parameters of the first mode of comprehensive MTMD control for floor slab installation on the third floor

Mass ratio μ	0.01				
TMD location	1	2	3	4	5
Frequency ratio r_{fk}	1.04	0.89	1.12	1.21	0.97
Mass m_s	2.97(t)	4.08(t)	2.56(t)	2.21(t)	3.46(t)
Stiffness k_s	1550.58 (kN/m)				
Damping c_s	4.7 (kN -sec/m)				
Mean-square ratio R_1	0.3699				

Table 2 Design parameters of the second mode of comprehensive MTMD control for floor slab installation on the third floor of the gymnasium

Mass ratio μ	0.02	
TMD location	6	7
Frequency ratio r_{fk}	1.05	0.97
Mass m_s	1.40(t)	1.65(t)
Stiffness k_s	1371.94 (kN/m)	
Damping c_s	3.29 (kN -sec/m)	
Mean-square ratio R_1	0.6104	

Table 3 Design parameters of the third mode of comprehensive MTMD control for floor slab installation on the third floor of the gymnasium

Mass ratio μ	0.02	
TMD location	8	9
Frequency ratio r_{fk}	0.970	1.055
Mass m_s	1.65(t)	1.40(t)
Stiffness k_s	3367.27 (kN/m)	
Damping c_s	3.42 (kN -sec/m)	
Mean-square ratio R_1	0.3706	

5. Conclusions

A new intelligent adaptive control system combining observation-based adaptive control and fuzzy adaptive control for composite structures with TM dampers is proposed. The main advantage is that the control structure does not need to know uncertain boundaries and the effect of disturbances is eliminated. It is shown that the D-stability of the original system can be studied by determining the D-stability of the corresponding slow and fast subsystems, if a perturbation parameter is sufficient. small. Then an algorithm is proposed to find an upper bound for a single perturbation parameter. Within this limit, the D-stability of the slow and fast subsystems can mean the D-stability of the original system. With the linear similarity matrix theory based on Lyapunov theory, it has been proved that the stability of the control system can be guaranteed. The simulation results show that the multiscale simulation method combines accuracy and high computational efficiency. The M-TMD system, by slightly reducing the critical load amplitude of the joint, can significantly improve the overall response of an uncontrolled structure. The goals of this paper are towards access to adequate, safe and affordable housing and basic services, promotion of inclusive and sustainable urbanization and participation, implementation of sustainable and disaster-resilient buildings, sustainable human settlement planning and manage. Therefore, the goal is believed to achieved in the near future by the ongoing development of AI and control theory.

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