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# Intelligent optimal grey evolutionary algorithm for structural control and analysis

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**Abstract.** This paper adopts a new approach in which nonlinear vibrations can be controlled using fuzzy controllers by optimal grey evolutionary algorithm. If the fuzzy controller cannot stabilize the systems, then the high frequency is injected into the system to assist the controller, and the system is asymptotically stabilized by adjusting the parameters. This paper uses the GM (grey model) and the neural network prediction model. The structure of the neural network is improved from a single factor, and multiple data inputs are extended to various factors and numerous data inputs. The improved model expands the applicable range of uncontrolled elements and improves the accuracy of controlled prediction, using the model that has been trained and stabilized by multiple learning. The simulation results show that the improved gray neural network model has higher prediction accuracy and reliability than the traditional GM model, improving controlled management and pre-control ability. In the combined prediction, the time series parameters and the predicted values obtained from the GM (1,1) (Grey Model of first order and one variable) are simultaneously used as the input terms of the neural network, considering the influence of the non-equal spacing of the data, which makes the results of the combined gray neural network model more rationalized. By adjusting the model structure and system parameters to simulate and analyze the controlled elements, the corresponding risk change trend graphs and prediction numerical calculation results are obtained, which also realize the effective prediction of controlled elements. According to the controlled warning principle and objective, the fuzzy evaluation method establishes the corresponding early warning response method. 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.

**Keywords:** composite structures; energy equations; intelligent control function; structural control; tuned mass damper

## 1. Introduction

In recent decades, many scholars have done a lot of theoretical and experimental research in the field of ANFIS tools for application in engineering problems. For example, Casciati (1997), Casciati and Casciati (2016, 2018), Casciati and Faravelli (2009) and Casciati *et al.* (2014, 2017) provide an artificial intelligence-based approach for applications in engineering and nonlinear structures. That is, among the results produced in the field, we can cite the establishment of implementing a fuzzy active control strategy of the civil engineering structures and learning procedure underlying ANFIS (adaptive-network-based fuzzy inference system) to automatic control and signal processing, particularly the nonlinear structures using the fuzzy control approach (Casciati and Faravelli 2016, Faravelli and Yao 1996, Jang 1993, Casciati and Faravelli 1996, Battista and Varela 2019). Therefore, here we propose a method to reduce the response of civil engineering structures and reduce the magnitude of stress cycles using a tuned mass damper control system (Safa *et al.* 2016, Fang *et al.* 2024, Cai *et al.* 2023, Tian *et al.* 2022, Wang *et al.* 2023a, b, Zheng *et al.* 2022, 2023a, b, Shariat *et al.* 2018).

Gray theory is a systematic analysis method and mechanism characterized by data scarcity and incomplete information. The study and analysis of the laws of change of things in the state of data scarcity and incomplete information provide methodological support for scientific understanding and research of gray problems (Wang *et al.* 2022a, b, She *et al.* 2023, Song *et al.* 2022, Ma and Hu 2022, Yang *et al.* 2024, Yu *et al.* 2022). Grey Model (abbreviated as GM) is a vital part of the whole grey analysis method, which is a simulation analysis using exponential or quasi-exponential laws. Due to its small amount of data required, low data requirements, and high prediction accuracy, it has been widely used in practice. In contrast, many researchers have conducted in-depth research on the GM model and proposed a series of improvement methods. The improvement of the model has improved the prediction ability of gray prediction in a particular application range, gradually improved the gray theory research structure, and promoted the further development of gray science (Bai *et al.* 2021, Chen *et al.* 2022, Liu *et al.* 2023, Gao *et al.* 2022, Hou *et al.* 2023a, b,

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Khan *et al.* 2024). This paper applies the gray prediction method to the study of civil safety risk, combines the control safety classification analysis method and system dynamics model, and analyzes the risk elements in the control system from the perspective of system and modeling through qualitative and quantitative research, improves the accuracy of gray prediction, enhances the early warning capability and effectiveness of civil safety risk, and thus provides a reliable method and theory for the first-line control units. This paper provides a reliable way and theoretical support for the risk management of frontline control units. This dissertation will follow the trend of changing the application mode of spatial information service from the simple invocation of a single service to the combination of multiple services to complete complex tasks and meet. The combination of the gray system model and neural network model mainly has several varieties, such as series type combination, parallel type combination, and embedding type combination. Hu *et al.* (2023) combined the gray system model with the neural network model and used the particle swarm algorithm to optimize the gray neural network's initial parameters to improve the model's robustness and accuracy. Wang *et al.* (2024) used the genetic-based algorithm to optimize the relevant parameters of the gray GM (1,1) model and, on this basis, combined with GA- BP to complete the task of predicting the flight safety demand of civil aviation. Yin *et al.* (2022), Li *et al.* (2022a, b, c) mainly used two prediction methods in the construction of the variable weight prediction model: one is the gray model method, and the other is the improved BP neural network method, which fully combines the advantages of both. Zhang *et al.* (2022a, b, 2023) fitted the historical data with the enhanced model, and the difference between the historical and original data constitutes the residual series; the artificial network model corrects the residual series. The primary data generated by the improved gray model prediction is combined with the fixed residual series.

In addition, intelligence is also a hot field that has attracted the attention of many researchers. This area contains many algorithms inspired by the little wisdom of Mother Nature. Generally speaking, swarm intelligence methods require evolutionary computation and imitate certain behaviors and survival skills of living things. In addition, this paper also applies the grey optimal algorithm to solve the control problem. Based on the above theory, the welding residual stress and the dynamic action applied to the bridge joint are obtained respectively. Based on the realization of the sub-model, a multi-scale model of the overall building model of the important nodes in the mid-span is jointly established. In addition, we will establish the motion equation of the control system with the new evolutionary fuzzy control. The entire methodology, along with estimating the required control capabilities, is performed using commercial software submodeling solutions. 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.

## 2. Structure problems and motion systems

Assume that the equation of motion can be written as

$$M\ddot{\bar{X}}(t) + C\dot{\bar{X}}(t) + K\bar{X}(t) = \bar{B}U(t) - M\bar{r}\ddot{x}_g \tag{1}$$

where $\bar{X} = [\bar{x}_1, \bar{x}_2, \cdots \bar{x}_n]^T \in R^n$ is an n-vector. M, C and K matrices are n by n mass, damping and stiffness parameters literally. The control input vector is U(t) corresponding to the input of the actuator. For controller design, the standard first-order equation of state corresponding to Eq. (1) is

$$\dot{X}(t) = AX(t) + BU(t) + E\ddot{x}_g \tag{2}$$

where

$$X^T = [\bar{X}^T \quad \dot{\bar{X}}^T] \tag{3}$$

where $\bar{X}(t) = [\bar{x}_1(t), \bar{x}_2(t) \cdots \bar{x}_n(t)] \in R^n$ is the n vector representing the alcove drift for the specified ith layer of cells. The dimensional control input vector U(t) corresponds to the actuator force (for example generated by an active solicitation system or an active actuator). It is a static model that ignores the dynamic equations of the actuator. These dynamic delay effects are described in the next section.

In controller analysis and scheme, the standard linear state equation corresponding to Eq. (1) is

$$\dot{X}(t) = AX(t) + BU(t) + E\ddot{x}_g$$

where state is an appropriate vector in structural mechanics. Passive dampers are often used as a mechanism to continuously absorb energy from a structure. This is a resilient device for damping the transient vibration of the structure without destabilizing the structure. Since available passive dampers do not always provide an adequate damping coefficient, speed feedback control systems are often used to mimic their behavior. The side-by-side speed feedback is robust. It doesn't break passive structures. When the juxtaposed velocity loops are closed with an appropriate gain, the structural responses tend to move further corresponding to the mechanism or towards the slightly attenuated open-loop zeros (Chen *et al.* 2022). These near-zero open-loop models simplify system I/O relationships, allowing more efficient model reduction later in controller design (Lyu *et al.* 2024, Lu *et al.* 2022, Peng *et al.* 2023, Zhao *et al.* 2024). Once you have a properly scaled model, you can use the LQG/LTR robust control method to get an active input design of the same order as the downscaled model.

## 3. Collocated velocity feedback

In structural mechanics, passive dampers are often used as a mechanism to continuously absorb energy from a structure. Once you have a properly scaled model, you can use the LQG/LTR robust controller to get an active design of the same order as the scaled model. After closing the parallel feedback loop, the linear state equation corresponding to Eq. (1) is

$$\dot{X}(t) = (A - BK_v C)X(t) + E\ddot{x}_g \tag{4}$$

where $C = [0 \ \ \bar{B}^T]$ is the location matrix representing collocated sensors and we additionally have the feedback gain

$$K_v = diag(K_{v1}, K_{v2}, \dots, K_{vi}, \dots, K_{vm}), \quad 1 \le i \le m \tag{5}$$

In this article, we want the reduced structural model to be (6). We then neglect the effect of seismic excitation and consider the full-order structural model G(s) given by

$$G(s) = \hat{G}_r(s) + \tilde{\Delta}_a(s) \tag{6}$$

$$\begin{aligned} \dot{X}(t) &= AX(t) + BU(t) \\ Y(t) &= CX(t) + DU(t) \end{aligned} \tag{7}$$

The vector contains the components to keep and then we divide the matrices A, B and C along X to get (8). Due to low frequency behavior in setting (9) for (10)

$$A = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix}, \quad B = \begin{bmatrix} B_1 \\ B_2 \end{bmatrix}, \quad C = [C_1 \ \ C_2]. \tag{8}$$

$$\dot{X}_2(t) = 0 \tag{9}$$

$$X_2(t) = -A_{22}^{-1}(A_{21}X_1(t) + B_{22}U(t)) \tag{10}$$

The reduced model of the rth order given by the method of truncation of the state space is (11). The reduced model of the rth order given by the method of truncation of the state space is (12)

$$\begin{aligned} X_1(t) &= (A_{11} - A_{12}A_{22}^{-1}A_{21})X_1(t) \\ &\quad + (B_1 - A_{12}A_{22}^{-1}B_2)U(t) \\ &\equiv \hat{A}_{11}X_1(t) + \hat{B}_1 U(t) \\ Y(t) &= (C_1 - C_2 A_{22}^{-1}A_{21})X_1(t) \\ &\quad + (D - C_2 A_{22}^{-1}B_2)U(t) \\ &\equiv \hat{C}_1 X_1(t) + \hat{D}U(t). \end{aligned} \tag{11}$$

$$\begin{aligned} \hat{G}_r(s) &\equiv T_r(A, B, C, D) \equiv \left(\hat{A}_{11}, \hat{B}_1, \hat{C}_1, \hat{D}\right) \\ &= \hat{C}_1\left(sI - \hat{A}_{11}\right)^{-1}\hat{B}_1 + \hat{D} \end{aligned} \tag{12}$$

Spatial state method is a simple but common idea for having reduced-order models because G(s) could have a limited number, there are thus have corresponding output of design. The theory of the reduced model depends on the chosen truncation implementation; For a controlled system to be useful, it must maintain stability and handle guaranteed errors.

Although there are an infinite number of different realizations in state space for one or more particular G patterns, an analysis of the state's degree of participation results in the balanced realization being considered the correct realization.

Consider the LQ (linear quadratic) problem

$$\min_{u \in L_2(-\infty, 0]} \int_{-\infty}^{0} U^T(t)U(t)dt \tag{13}$$

subject to

$$\dot{X}_b = A_b X_b + B_b U(t) \tag{14}$$

with

$$X_b(0) = X_{0b}. \tag{15}$$

From the result of Zhou *et al.* (2024), we can conclude that

$$\begin{aligned} &\max_{u \in L_2(-\infty, 0]; X(0) = X_{0b}} \frac{\int_{-\infty}^{0} Y^T(t)Y(t)dt}{\int_{-\infty}^{0} U^T(t)U(t)dt} \\ &= \frac{X_{0b}^T Q X_{0b}}{X_{0b}^T P^{-1} X_{0b}} = \frac{X_{0b}^T \Sigma X_{0b}}{X_{0b}^T \Sigma^{-1} X_{0b}} = \sum_{n=1}^{n} \sigma_i^2 X_{0b_i}^T X_{0b_i} \end{aligned} \tag{16}$$

Moreover, the double-tailed sum satisfies the norm of bounded infinity (Liang *et al.* 2024a, b, Cao *et al.* 2023, Guo *et al.* 2023, Li and Sun 2021)

$$\begin{aligned} \left\|\tilde{\Delta}_a(s)\right\|_\infty &\equiv \left\|G(s) - \hat{G}_r(s)\right\|_\infty \\ &\le 2(\sigma_{r+1} + \sigma_{r+2} + \dots + \sigma_n) \end{aligned} \tag{17}$$

where the infinity norm is defined as

$$\left\|\tilde{\Delta}_a(s)\right\|_\infty \equiv \sup_\omega \bar{\sigma}\left[\tilde{\Delta}_a(j\omega)\right]. \tag{18}$$

Recall that singular values of matrix A are the square roots of the eignvalues of $A * A$; i.e.

$$\sigma_i^2(A) = \lambda_i(A * A), \tag{19}$$

where A* is the complex conjugate transpose of A (Alves *et al.* 2023, Di *et al.* 2023, Li *et al.* 2023, Liu *et al.* 2021a, b, 2024). And $\bar{\sigma}(A)$ and $\underline{\sigma}(A)$ denote the maximum and minimum singular value of A respectively.

The following lemma and definition quantifies the tolerable size using a singular value and relates it to the achievable bandwidth of the control loop.

Lemma 1: Suppose that $\tilde{\Delta}_a(s)$ there are no unstable poles and the controller stabilizes the reduced-order structural model. Then (20) shows that the frequency must be non-uniform then the controller K would decrease vibrations of the structural model G(s) in full order and the robust frequency is (21)

$$\frac{\bar{\sigma}\left(\tilde{\Delta}_a(j\omega)\right)}{\underline{\sigma}\left(\hat{G}_r(j\omega)\right)}\bar{\sigma}\left[\hat{G}_r(j\omega)K(j\omega)\left(I + \hat{G}_r(j\omega)K(j\omega)\right)^{-1}\right] < 1 \tag{20}$$

$$\omega_r \equiv max\left\{\omega \middle| \underline{\sigma}\left(\hat{G}_r(j\omega)\right) \ge \bar{\sigma}\left(\tilde{\Delta}_a(j\omega)\right)\right\} \tag{21}$$

The importance of bound is based on robustness concept, i.e.

$$\underline{\sigma}\left(\hat{G}_r(j\omega)K(j\omega)\right) \gg 1, \tag{22}$$

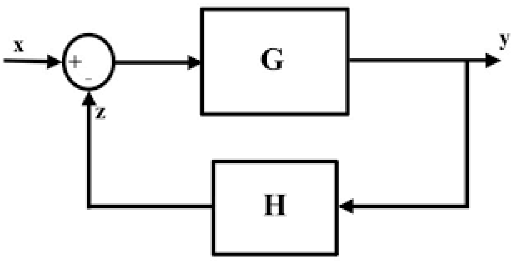


Fig. 1 The closed-loop configuration of the feedback control system

for all

$$\omega < \omega_B \tag{23}$$

$$\bar{\sigma}\left\{\hat{G}_r(j\omega)K(j\omega)[I + \hat{G}_r(j\omega)K(j\omega)]^{-1}\right\} \approx 1 \tag{24}$$

and

$$\underline{\sigma}\left(\hat{G}_r(j\omega)\right) > \bar{\sigma}\left(\tilde{\Delta}_a(j\omega)\right). \tag{25}$$

Fig. 1 shows the configuration of a closed loop control system with a K(s) controller to be designed for the reduced order model. Therefore, the following equation can be deduced

$$\frac{y(S)}{x(S)} = \frac{G(S)}{[1 - H(S) \times G(S)]} \tag{26}$$

The global designed controller is

$$K(s) = \left(\frac{I}{s}\right) K_{\frac{LQG}{LTR}}(s) \tag{27}$$

We then define (28) as a controlled system having a reduced state space design shown as (29)-(31).

$$G_a(s) = \hat{G}_r(s)\left(\frac{I}{s}\right) \tag{28}$$

$$\dot{X}_a = A_a X_a(t) + B_a U_a(t) \tag{29}$$

$$Y(t) = C_a X_a(t) \tag{30}$$

$$G_a(s) = C_a(sI - A_a)^{-1} B_a \tag{31}$$

where

$$X_a^T = (\underbrace{x_1, \dots, x_m}_{int\,egrator-states}, \underbrace{x_{m+1}, \dots, x_{m+r}}_{reduced-mod\,el-states}) \tag{32}$$

$$A_a = \begin{bmatrix} 0 & 0 \\ \hat{B}_{b_1} & \hat{A}_{b_{11}} \end{bmatrix}, \quad B_a = \begin{bmatrix} I \\ 0 \end{bmatrix}, \quad C_a = [\hat{D}_{b_1} \square \hat{C}_{b_1}] \tag{33}$$

The grey wolf is a carnivorous canine, their characters specialize in agile, rapid and long-range galloping, and possess majestic adaptability for the environment. Inheriting similar the grey wolf's capability, the GWO possessed the optimization procedure of encircling, social stratification, and attacking prey. The improved grey model-based fuzzy neural network scheme-algorithm combines the grey evolved algorithm and the laypunov based model based neural network scheme control laws with a greedy strategy.

## 4. Robust gray evolutionary controller

Gray wolves are carnivorous dogs with an agile personality, are good at fast and long-distance running, and are highly adaptable to the environment. GWOs inherit similar capabilities to gray wolves, optimizing the procedures for mobbing prey, forming social hierarchies, and aggression, and we conclude that:

(1) Social Hierarchy: Gray wolves have hierarchical social relationships because they live primarily in groups called packs. The social ranks of gray wolves from high to low are $\alpha$, $\beta$, $\delta$ and $\omega$. At the top of the social hierarchy, $\alpha$ wolves are pack leaders. As wolves, their main responsibility is $\alpha$ to make decisions regarding predation and other systemic activities. For the second social hierarchy, wolves $\beta$ help wolves, obey $\alpha$ wolves, and manage all wolves that are not wolves $\alpha$. The wolf is $\delta$ the third social class in the hierarchy after the $\beta$ wolf $\alpha$. This $\delta$ wolf may dominate the rest. Wolves are the lowest social class, and $\omega$ all other social classes follow these wolves.

(2) Rounding up prey: Gray wolves like to round up prey. These mathematical models of this behavior can be described as follows.

$$\vec{X}(t+1) = \vec{X}_P(t) - \vec{A}\vec{D}$$
$$\square$$
$$\vec{D} = |\vec{C}\vec{X}_P(t) - \vec{X}(t)|$$
$$\vec{X} = 2\vec{a}\vec{r}_1 - \vec{a}$$
$$\vec{C} = 2\vec{r}_2$$

where $X$ presents the grey wolf's position vector, and$X_P$ presents the prey's position vector, $t$ is the current iteration number, A and C coefficient vectors, and a convergence factor which diminishes linearly from 0 to 2 during its iterative procedure, and $r_1$ and $r_2$ are vectors in the random range of [0, 1].

(3) Hunting: the grey wolf pack could discriminate the prey's positions as well as encircle prey. The seeking procedure is primarily dominated by the grey wolf $\alpha$. It is suppose that the $\alpha$, $\beta$ and $\delta$ wolves can powerfully detect the prey's potential positions than the rest of the pack in order to simulate the hunting behaviour through mathematically. The newly present positions of the $\delta$, $\beta$ and $\alpha$ wolves are retained in each iteration, and renovating other wjich is including $\omega$ positions according to these ruling positions. The mathematical model is as follows:

Fig. 2 displays how a seeking agent renovates its $\delta$ positions depending on the $\alpha$, $\beta$ and $\delta$ positions within a 2D seeking range. R presents the radius of the prey's predicted position. The final position has been a random point under to condition of a circle which is determined by the positions of $\delta$, $\beta$ and $\alpha$ in the seeking range. That is, $\alpha$, $\beta$ and $\delta$ predict the prey's position, and other wolves renovate the positions randomly around this prey.

(4) Searching prey (called exploration): In the GWO algorithm, the seeking procedures initial with creating a stochastic grey wolves pack (candidate solutions). Through the iterations course, the $\alpha$, $\beta$ and $\delta$ wolves will be predicting the prey's predictable position.

(5) Attacking prey (exploitation): As previously discussed, these grey wolves complete hunting through attacking that prey while it suspends moving. To modelling mathematics for the course of approaching that prey, the study diminishes the value $a \rightarrow$. Paying attention to the undulation scope of $A \rightarrow$ it is also diminished by regulating $a \rightarrow$. While the stochastic values of $A \rightarrow$ they are in the scope of [1,1], the newly location of a seeking agent could be anywhere amid the present location and the prey's location.

In this paper, the improved Lyapunov evolutionary neural network GWO is used for geometric optimization design. The improved fuzzy neural network scheme algorithm based on gray model combines gray evolutionary algorithm and neural network scheme control law based on Lapnov model with greedy strategy. The algorithm is a bionic algorithm, which has the characteristics of fast convergence, easy parameterization and memory. Gray Liampunov's nonlinear neural network-based algorithmlearns how wolves forage, randomly generates initial values in the solution space to simulate the wolf's position, and

$$\dot{x}_R(t) = \frac{\sum_{i=1}^{r} w_i(x_R(t), \alpha_m, \beta_m)\{A_i(\alpha_m, \beta_m)x_R(t) + B_i(\alpha_m, \beta_m)u_R(t)\}}{\sum_{i=1}^{r} w_i(x_R(t), \alpha_m, \beta_m)} \tag{35}$$

uses encirclement and attack formulas to optimize estimated solutions. The improved Laypunov criterion of GWO neurons changes the convergence coefficient, increases the global search share, prevents it from entering the optimal solution region, increases the memory capacity, improves the convergence efficiency, and improves the search efficiency by increasing the position weights, making the search direction more accurate is becoming. Be clear and use a greedy strategy to avoid excessive and useless searches. Numerical analyzes of the function and structure show that the proposed linear differential model based on digital neural network using GWO can achieve good results.

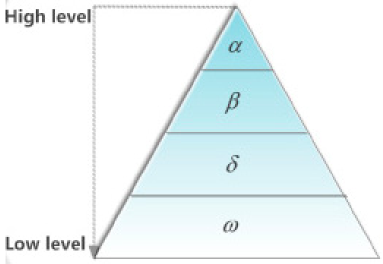


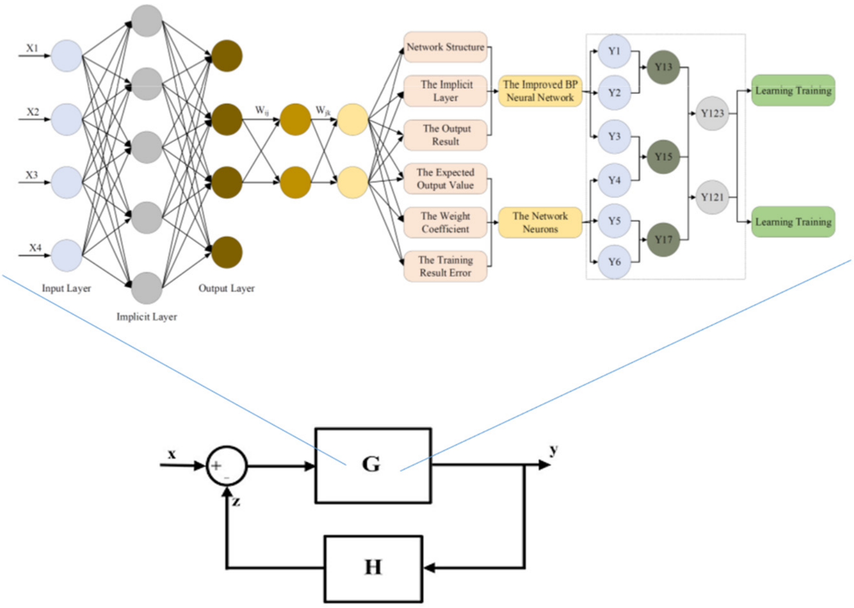
Fig. 2 A seeking hierarchy

To explain the structure of the operating system in this publication, the remainder of the book is divided into two parts. The Takagi fuzzy model is established and the fuzzy controller is designed using the PDC method, and the stability criterion is established to evaluate whether the closed-loop fuzzy system is stable.

Closed-loop fuzzy system:

To facilitate stability analysis, we $Q = P^{-1}$ can assume and further define as follows, $W_i = K_iQ$ so $Q > 0$ yes $K_i = W_iQ^{-1}$.

Lemma 2 (Wang *et al*. 2022a, b) The closed-loop



Cao *et al*. 2023 Fig. 3 Improved gray evolutionary neural network control process in control plant (Casata *et al*. 2017) ambiguity, if present, is large and stable via the PDC, allowing the condition to be satisfied.

$$A_i^T + A_i Q - B_i W_i - W_i^T B_i^T < 0 \tag{34}$$

Build the TS fuzzy model of the relaxed model. The fuzzy controller is then retrieved through the PDC scheme.

The ith rule of the fuzzy mitigation model is $F_R(0;0)$ expressed as

Control rule i

IF $x_{R1}(t)$ is $M_{iK}^R(\alpha_m,\beta_m) \dots M_{i1}^R(\alpha_m,\beta_m)$ and $x_{Rk}(t)$

Then

$$u_R(t) = -K_i(\alpha_m,\beta_m)x_R(t) \qquad i = 1,2,\dots,r \tag{36}$$

From the above discussion, it can be inferred that if the frequency of adjustment is high enough and a suitable fuzzy function is decided, the trajectories of the designed fuzzy relaxed system and the original nonlinear system will be relatively close which means solution to be feasible. From now on, we no longer discuss the stability of closed-loop dithering chaotic systems, but the stability of $N(C;d)$ closed-loop fuzzy mitigation systems $F_R(C;0)$. Therefore, the stability criteria are listed below.

The improved BP neural network has a multilayer network structure consisting of many neurons or nodes interconnected with each other. The model contains forward transfer and reverses feedback. In forward transfer, the input vector enters from the input layer, goes through the action of the implicit layer, and finally reaches the output layer and outputs the result. Suppose the output result is not the expected output value. In that case, the reverse feedback starts, and the weight coefficient and output threshold are adjusted according to the training result error, which makes the output result close to the expected output value. The structure diagram of the improved BP neural network is shown in Fig. 3.

## 5. A numerical example

The improved BP neural network can be considered a complex nonlinear function. Due to the complex relationship between the network neurons, it is generally difficult to derive a specific function relationship formula, but the network has the role of associative memory. Through continuous learning training, the operation process and the way are remembered in the network. The learning training process will stop when the movement reaches a certain number of times and meets specific accuracy requirements. When the training gets a certain number of times and meets specific accuracy requirements, the learning and training process controls, and a stable neural network structure is formed, which can be considered as seeking a nonlinear function with a relatively high fitting degree and using this training network to make relevant predictions, the prediction results obtained have higher accuracy and better prediction effect. Based on the input and output vectors of the network structure, the number of nodes in the input layer $n$, the number of nodes in the output layer $m$ and the number of nodes in the hidden layer $l$ are generally obtained on the basis of empirical formulas. To illustrate the application of the proposed design methodology, the controller design procedure was used. A model with pooled parameters was used for the simulations. The schema of the grouped model is written in terms of relative ground motion. We can have system matrix for mass and stiffness.

$$M^{-1}K = \begin{bmatrix} k_1/m_1 & -k_2/m_1 & 0 & 0 & 0 & 0 \\ -k_1/m_1 & (k_2/m_1)+(k_2/m_2) & -k_3/m_2 & 0 & 0 & 0 \\ 0 & -k_2/m_2 & (k_3/m_2)+(k_3/m_3) & -k_4/m_3 & 0 & 0 \\ 0 & 0 & -k_3/m_3 & (k_4/m_3)+(k_4/m_4) & -k_5/m_4 & 0 \\ 0 & 0 & 0 & -k_4/m_4 & (k_5/m_4)+(k_5/m_5) & -k_6/m_5 \\ 0 & 0 & 0 & 0 & -k_5/m_5 & (k_6/m_5)+(k_6/m_6) \end{bmatrix}.$$

Similarly, $M^{-1}C$ and $\ddot{x}_g$ will be the earthquake ground acceleration. The control influence matrix $\bar{B}$, depends on the number and locations of actuators used. We will have

$$M^{-1}\bar{B} = \begin{bmatrix} 1/m_1 & -1/m_1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1/m_3 & -1/m_4 & 1/m_4 & 0 \end{bmatrix}.$$

The standard approach to this problem is to form uncontrolled structural models in the extended state.

$$\begin{bmatrix} \dot{X}(t) \\ \dot{u}(t) \end{bmatrix} = \begin{bmatrix} A & B \\ 0 & -b \end{bmatrix} \begin{bmatrix} X(t) \\ u(t) \end{bmatrix} + \begin{bmatrix} 0 \\ b \end{bmatrix} v(t) + \begin{bmatrix} E \\ 0 \end{bmatrix} \ddot{x}_g.$$

Since obtained the proposed fuzzy TMD parameters from the optimization code described in section 2 that is stiffness, damping, mass ratio and modal transfer function. According to proposed ANFIS modified tool for Structural Safety (Cao *et al.* 2023), choosing a positive matrix and input force is an important issue that needs to be addressed. In this paper, the fitness function is designed based on the stability criterion obtained from the LMI conditions of the Lyapunov mode. The logical AND function in the function is used to examine the solutions to obtain control parameters and weighting matrix by grey neural networks from Lemma 1 and Lemma 2 as follows.

$$G = \frac{1}{2}\sum_{l=1}^{2} A_l - B_l F_l = \begin{bmatrix} -22.5251 & -24.5368 \\ 1 & 0 \end{bmatrix},$$
$$F_1 = [-1.0751 \quad -1.0301], \quad F_2 = [0.6675 \quad 0.8467].$$

The Fig. 4 shows the simulated lump mass and Fig. 5 displayed the dynamic response of each joint with presence of TMD and without it. The control performance of the proposed fuzzy-control TMD system is evaluated via the reduction of acceleration response of nonlinear structures by comparing them to Setra and Hivoss guidelines. The dynamic response is displayed in Fig. 6 and also Table 1 is

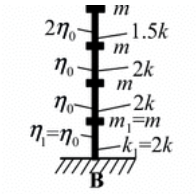


Fig. 4 Schematic representation of a structure modeled on a cross-sectional frame

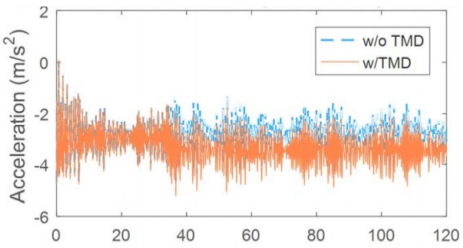


Fig. 6 Acceleration response at the center of the structure

summarized the acceleration response of four joints.

## 6. Conclusions

Because highly flexible structures are subject to natural excitation forces such as earthquakes and strong winds, it is easy to cause structural damage. The seismic design of highly flexible structures has attracted considerable attention from scholars and experts in recent years, and the concept of structural control has been widely studied, and passive, active, and hybrid structural controls have been proposed. Modern control theory has been practically applied in various industrial control. The purpose of this paper is to develop the fuzzy control theory and apply it to the structure control system, so that the structure can still ensure its stability and safety under the action of intense force. First deduce the governing equation of the bridge under the action of a constant moving concentrated load, then establish the state equation of the bridge structure control system according to the modal control method, and use the fuzzy control method and the fuzzy sliding mode control method as the control of the structure, to explore the bridge structure.

The dynamic response of the structure to the external force. The simulation results prove that the fuzzy control theory can be applied to the bridge structure control system. The two control methods used in this paper are within the controllable range. It is found that the bridge structure system can be well controlled under different damping ratios and different starting points under severe external force and system parameter changes. Comparing with other control methods, it is found that this method is superior to traditional structural control, and it is more economical and practical in terms of providing control power, and it can also avoid energy waste. 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.

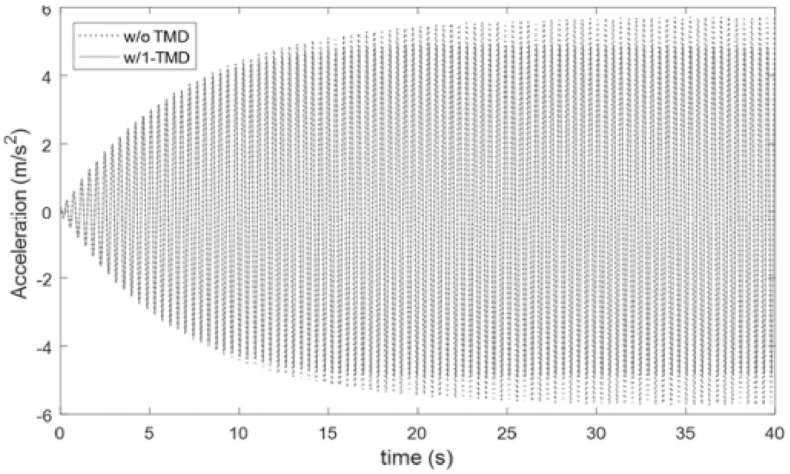


Fig. 5 μ = 0.1% Vertical Peak acceleration w/o MTMD and w/1-TMD

Table 1 Control performance of fuzzy evolutionary algorithmic TMD

| Joint responses | Lateral peak acceleration $(\mathrm{m/s^2})$ | | Vertical peak acceleration $(\mathrm{m/s^2})$ | |
|---|---|---|---|---|
| | W/o TMD | W/TMDs | W/o TMD | W/TMDs |
| A | 0.162 | 0.0923(-43%) | 2.525 | 0.926(-63.6%) |
| B | 0.3383 | 0.16851(-50%) | 4.618 | 1.934(-58.12%) |
| C | 0.923 | 0.55 (-40.4%) | 4.642 | 2.02 (-56.48%) |
| D | 0.853 | 0.356(-58.27%) | 4.595 | 1.94 - (57.7%) |

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