Data Driven Vibration Control: A Review

Weiyi Yang, Shuai Li, *Senior Member, IEEE*, and Xin Luo, *Senior Member, IEEE*

***Abstract*—With the ongoing advancements in sensor networks and data acquisition technologies across various systems like manufacturing, aviation, and healthcare, the data driven vibration control (DDVC) has attracted broad interests from both the industrial and academic communities. Input shaping (IS), as a simple and effective feedforward method, is greatly demanded in DDVC methods. It convolves the desired input command with impulse sequence without requiring parametric dynamics and the closed-loop system structure, thereby suppressing the residual vibration separately. Based on a thorough investigation into the state-of-the-art DDVC methods, this survey has made the following efforts: 1) Introducing the IS theory and typical input shapers; 2) Categorizing recent progress of DDVC methods; 3) Summarizing commonly adopted metrics for DDVC; and 4) Discussing the engineering applications and future trends of DDVC. By doing so, this study provides a systematic and comprehensive overview of existing DDVC methods from designing to optimizing perspectives, aiming at promoting future research regarding this emerging and vital issue.**

***Index Terms*—Data driven vibration control (DDVC), data science, designing method, feedforward control, industrial robot, input shaping, optimizing method, residual vibration.**

I. Introduction

IN real scenes, the system model inevitably suffers from uncertainty due to the parametric inaccuracy and internal/external disturbance [1]–[3]. To address such issue, data driven vibration control (DDVC) arouses extensive research efforts and becomes an important topic in the area of vibration control [4]. Differently from model-based control approaches and feedback control returning output command, it designs a controller directly from the input-output data of the system [5]–[7].

With the rapid progress and wide applications of the robot vibration control, it developed rapidly in the past decade [8], [9]. Ma *et al*. [10] provide an overview of research endeavors in the dynamics and control field utilizing data-driven approaches, including structural optimization, active vibration control and system identification, etc. Qin and Xin [11] introduce a data-driven H_∞ vibration control algorithm to address the challenges of active suspension vibration control, and reveal the algorithm's insensitivity to data size through a quantitative study of two key parameters. Liu *et al*. [12] propose an accurate and efficient approach with a gated recurrent unit (GRU) data-driven model, which predicts the dynamic behavior of the nonlinear vibratory system and is proved by Low evaluation metrics and $\mathbb{R}^2$ close to 1. To date, in response to the demands of industrial applications, hundreds of DDVC approaches have been designed and proposed [13]–[17] and are predominantly implemented by feedforward control.

Input shaping (IS), is a typical feedforward open-loop control technique used for residual vibration control [18], it not only shapes the input command directly for efficient and easy implementation, but also evades the expensive device for measuring output command like feedback control [19], on the other hand, no longer suffers the burden in structural mass caused by adding damping and stiffness [20]. Hence, IS is highly effective in high-speed motion and high-precision positioning systems, and is of great significance for the following reasons:

1) Accurate motion analyses are limited owing to the increasing complicated robotic operation and system structure. Fortunately, IS dispenses with a precise mathematical system model, which opens an opportunity to conduct research on DDVC; and

2) Advanced control methods are difficult to implement in practical engineering due to the restriction of achievable sampling rate, sensor requirements and control structure. Therefore, it is extremely interesting to perform IS without feedback quantum and special measuring instruments.

In recent years, IS has proven to be primarily implemented and highly efficient in DDVC, which generates a series of self-canceling impulses [21], e.g., industrial robot [22], crane [23], computer numerical control (CNC) machine tools [24]–[28] and pick and place in the electronics industry [29]. Additionally, it exhibits superior vibration suppression capabilities compared to traditional filtering methods, i.e., low-pass filtering [30] and notch filtering [31]. Another open-loop control method commonly used in addressing vibration control problem is trajectory smoothing [32]. Diverging from IS, which focuses on input impulse design, trajectory smoothing is model-dependent, and is geared towards modifying the motion trajectory of a system or robot, thereby ensuring a smooth, stable trajectory that aligns with specific requirements [33].

Manuscript received December 5, 2023; revised February 10, 2024; accepted March 20, 2024. This work was supported by the National Natural Science Foundation of China (62272078). Recommended by Associate Editor Jinhua She. *(Corresponding authors: Shuai Li and Xin Luo.)*

Citation: W. Yang, S. Li, and X. Luo, "Data driven vibration control: A review," *IEEE/CAA J. Autom. Sinica*, vol. 11, no. 9, pp. 1898–1917, Sept. 2024.

W. Yang is with the Chongqing Institute of Green and Intelligent Technology, Chinese Academy of Sciences, Chongqing 400714, and also with the Chongqing School, University of Chinese Academy of Sciences, Chongqing 400714, China (e-mail: yangweiyi@cigit.ac.cn).

S. Li is with the Faculty of Information Technology and Electrical Engineering, University of Oulu, Oulu 90570, and also with the VTT-Technology Research Center of Finland, Oulu 90570, Finland (e-mail: shuai.li@oulu.fi).

X. Luo is with the College of Computer and Information Science, Southwest University, Chongqing 400715, China (e-mail: luoxin@swu.edu.cn).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/JAS.2024.124431

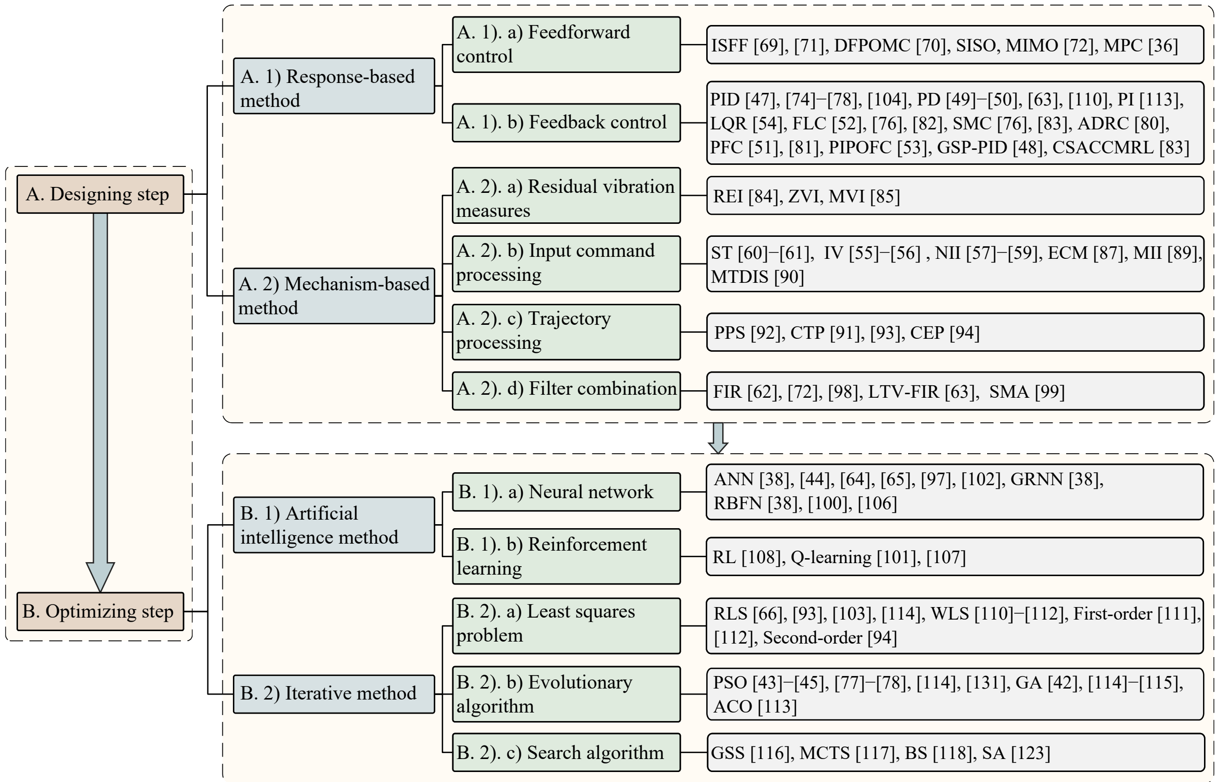


Fig. 1. Classification of DDVC.

Moreover, filtering techniques and generating new trajectories [34] are frequently applied in trajectory smoothing. Collectively, IS has played a crucial role in DDVC.

Therefore, IS technology, as an emerging topic in academic communities, has attracted lots of attention. Piedrafita *et al*. [35] present a comprehensive Simulink implementation of IS and propose seven input shapers to verify the control efficiency, which greatly reduce vibration, between 47% and 81% the transient and up to 99% the residual. Ghorbani *et al*. [36] conduct a brief overview of three standard input shapers and make comparisons with various frequencies for the first time. Bilgic *et al*. [37] present a brief review of IS methods and propose a fuzzy logic-based decision support system (FL-DSS) to provide assistance in the selection of suitable input shapers. Yavuz and Beller [38] review the IS and hybrid control methods used in cranes, and demonstrate artificial intelligence assisted transport operations on a simple pendulum, which contributes to the overall performance for residual vibrations elimination, strengthening the impact of intelligent control in DDVC.

Notably, single open-loop controllers often exhibit limited control performance. Therefore, DDVC is critical to the control capability and robustness problem against model uncertainty [39]–[41]. Yi *et al.* [42] utilize genetic algorithm (GA) to identify input shaper parameters, mitigating the influence of uncertainties in system parameters. Xu *et al*. [43] incorporate the particle swarm optimization (PSO) algorithm into conventional ZVD formers, demonstrating promising simulation and experimental results in nonlinear systems. However, as system parameters shift, the repetitive iterative processes diminish the controller's efficiency, and these evolutionary algorithms are also unsuitable for real-time optimization. To address this issue, Ramli *et al*. [44] propose a UMZV shaper using an ANN trained by PSO algorithm. Specifically, it involves offline construction of optimal shaper parameter sets corresponding to different system parameters, enabling real-time prediction and direct updates of the shaper's parameters.

In order to further enhance real-time system robustness and shorten optimization duration, Tang *et al.* [45] devise a control scheme based on PSO and adaptive techniques via offline and online dual optimization, and the simulation results demonstrate higher robustness and effectiveness. For multi-modal systems, Jaafar *et al*. [46] propose a model reference command shaping (MRCS) method based on estimating the system poles, which operates independently without relying on precise system parameters or any vibration feedback sensors. Although practical experiments verify its effectiveness and robustness, it is confined to vibration control, lacking the capability to drive the system to various desired positions. In view of this limitation, Jaafar *et al*. [47] introduce a combined feedforward and feedback MRCS-PID controller. In addition to employing a proportional-integral-derivative (PID) controller, simultaneous parameter tuning is realized through PSO, striving for accurate system positioning and effective vibration control.

Motivated by the above mentioned successes of residual vibration control, DDVC has attracted widespread attention, yielding a rapidly increasing number of related studies. However, a survey regarding its state-of-the-art remains missing. This paper presents a comprehensive survey of existing DDVC methods. As shown in Fig. 1, existing DDVC methods are categorized from designing steps to optimizing steps.

They can be subdivided into a) Response-based designing; b) Mechanism-based designing; c) Artificial intelligence method; 4) Iterative method. This work intends to make the following contributions.

1) Introducing the theory of IS and several standard shapers;

2) Summarizing the progress of IS method from designing to optimizing perspectives, where the state-of-the-art is carefully reviewed and categorized;

3) Summarizing the typical evaluation metrics of DDVC models, as well as the control metrics for comparing different DDVC methods; and

4) Discussing the DDVC development trends.

Section II details the theory. Section III reviews state-of-the-art DDVC methods. Section IV summarizes typical metrics for DDVC. Section V discusses DDVC's applications and future trends. Eventually, Section VI draws the conclusions.

II. IS Theory

This section covers: 1) The introduction of IS basis; and 2) The residual vibration control from designing to optimizing steps. Abbreviations adopted in this paper are given in Table I.

A. IS Basis

1) Theory

As a feedforward open-loop control method, input shaper consists of a series of impulses, and reduces vibration by convolving input commands. More specifically, its design varies with the system characteristics, resulting in different amplitudes and time delays of impulses. The basic rule and process of shaping work is shown in Fig. 2.

Since any system dominated by a single order vibration mode can be approximated by a second-order system, the transfer function can be expressed as

$$G(s) = \frac{\omega_n^2}{s^2 + 2\zeta\omega_n s + \omega_n^2} \tag{1}$$

where s is a complex variable, ω_n is the undamped natural frequency and ζ is the damping ratio. Note that the shapers need to identify these two modal parameters in advance and the traditional methods are: a) Establishing the system dynamic model and solving the dynamic equation; b) Hammer method or other modal experiments; and c) Finite element analysis method [48]. Thus, the unit impulse input response is given as

$$\omega(t) = \frac{\omega_n}{\sqrt{1-\zeta^2}} e^{-\zeta\omega_n(t-t_n)} \sin\omega_d(t-t_n) \tag{2}$$

where ω_d is the damped frequency, and$\omega_d = \omega_n\sqrt{1-\zeta^2}$. Hence, mathematical equation for input shaper is given as

$$F(s) = \sum_{i=1}^{n} A_i e^{-t_i s} \tag{3}$$

where A_i and t_i are the amplitudes and time locations of the impulses, n is the number of impulses in the impulse sequence. To obtain the system response, under the conversion of trigonometric function difference formula and trigonometric auxiliary angle, it can be expressed as

$$\begin{aligned} y(t) = {} & \frac{\omega_n}{\sqrt{1-\zeta^2}} e^{-\zeta\omega_n t} \\ & \times \sqrt{\left(\sum_{i=1}^{n} A_i e^{\zeta\omega_n t_i}\cos\omega_d t_i\right)^2 + \left(\sum_{i=1}^{n} A_i e^{\zeta\omega_n t_i}\sin\omega_d t_i\right)^2} \\ & \times \sin(\omega_d t - \varphi) \end{aligned} \tag{4}$$

where φ is given as

$$\varphi = \arctan\frac{\sum_{i=1}^{n} A_i e^{\zeta\omega_n t_i}\sin\omega_d t_i}{\sum_{i=1}^{n} A_i e^{\zeta\omega_n t_i}\cos\omega_d t_i}. \tag{5}$$

Note that the addition of impulse response becomes the total system response. The residual vibration ratio (ratio of (4) to (2)) that results from a sequence of impulses is defined as

$$V(\zeta,\omega_n) = e^{-\zeta\omega_n t_n}\sqrt{C^2(\zeta,\omega_n) + S^2(\zeta,\omega_n)} \tag{6}$$

where $C(\zeta, \omega_n)$ and $S(\zeta, \omega_n)$ are given as

$$\begin{cases} C(\zeta,\omega_n) = \sum_{i=1}^{n} A_i e^{\zeta\omega_n t_i}\cos\omega_d t_i \\ S(\zeta,\omega_n) = \sum_{i=1}^{n} A_i e^{\zeta\omega_n t_i}\sin\omega_d t_i. \end{cases} \tag{7}$$

By setting (7) equal to zero, the impulse amplitudes and time locations leading to zero residual vibration can be achieved. However, more restrictions on the impulses should be placed, or the solution will converge to zero or infinity [49]. The following section details several typical shapers and their derivations.

2) Typical Input Shapers

a) Zero vibration (ZV) shaper: ZV shaper is the simplest input shaper and consists of only two impulses [50]. For the second order system in (1), the ZV input shaper is expressed as

$$F(s) = A_1 + A_2 e^{-t_2 s}. \tag{8}$$

To avoid the trivial solution of all zero-valued impulses and to obtain a normalized result, the sum of the impulses should be one [51]. Besides, t_1 is set to zero for the shortest shaping time, the constraint is expressed as

$$\begin{cases} t_1 = 0 \\ A_1 + A_2 = 1. \end{cases} \tag{9}$$

Based on (7), they are set as

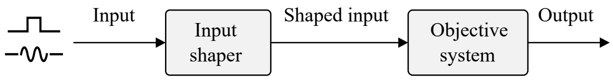
$$\begin{cases} A_1 + A_2 e^{\zeta\omega_n t_2}\cos\omega_d t_2 = 0 \\ A_2 e^{\zeta\omega_n t_2}\sin\omega_d t_2 = 0 \end{cases} \tag{10}$$

where $\omega_n t_2 = n\pi$, $n = 1,2,\ldots$, choosing the smallest value for t_2, the amplitude and time delay are given as

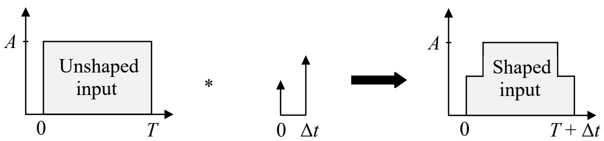
$$\begin{cases} A_1 = \dfrac{e^{\frac{\zeta\pi}{\sqrt{1-\zeta^2}}}}{1 + e^{\frac{\zeta\pi}{\sqrt{1-\zeta^2}}}}, \quad A_2 = \dfrac{1}{1 + e^{\frac{\zeta\pi}{\sqrt{1-\zeta^2}}}} \\ t_1 = 0, \quad t_2 = \dfrac{\pi}{\omega_d}. \end{cases} \tag{11}$$

TABLE I
ADOPTED ABBREVIATIONS

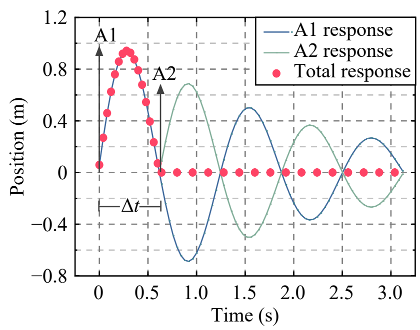
Term	Explanation	Term	Explanation
ACO	Ant colony optimization	MTCA	Minimum time control algorithm
ADRC	Active disturbance rejection control	MTDIS	Modified zero-time delay IS
ANN	Artificial neural network	MTS	Maximum transient swing
APIDLNN	Adaptive PID like neural network	MVI	Minimum vibration and integral
BS	Bayesian search	NA	Newton algorithm
CEE	Contour error estimation	NHMMIS	Negative-impulse hybrid multiple-modal input shaper
CEP	Contour error precompensation	NII	Negative impulse input
CNC	Computer numerical control	NN	Neural network
CSACCMRL	Clonal selection algorithm combining cloud model and reverse learning	NTVS	Nonlinear time-varying systems
CTP	Cartesian trajectory planning	NZV	Negative zero vibration
DDVC	Data-driven vibration control	OATF	Optimal arbitrary time-delay filter
DFPOMC	Data-driven feedforward parameter tuning optimization method under actuator constraints	OIS	Optimal input shaper
DOF	Degree of freedom	PA	Prediction accuracy
DZV	Dynamic zero-vibration	PD	Proportional-derivative
ECM	Error compensation method	PFC	Predictive functional control
EI	Extra insensitivity	PID	Proportional-integral-derivative
EKF	Extended Kalman filtering	PIPOFC	Position-input position-output feedback controller
ETM	Equal shaping-time and magnitude	PPS	Predictive path scheduling
FIR	Finite impulse response	PSO	Particle swarm optimization
FLC	Fuzzy logic control	QP	Quadratic programming
FL-DSS	Fuzzy logic-based decision support system	R^2	R-squared
FRF	Frequency response function	RAE	Relative absolute errors
GA	Genetic Algorithm	RBFNN	Radial basis function neural network
GD	Gradient descent	REI	Residual energy index
GRNN	General regression NN	RL	Reinforcement learning
GRU	Gated recurrent unit	RLIS	RL-based optimization method for IS
GSP	Generalized smith predictor	RLS	Recursive least square
GSS	Golden section search	RM	Robustness measures
H_∞	H-infinity	RMMBC	Reference model matching backstepping controller
HDD	Hard disk drive	RMSE	Root mean squared error
IAE	Integral absolute error	RRT	Rapidly exploring random tree
IS	Input shaping	RZV	Robust zero-vibration
ISFF	Input shaping joint feedforward	SD	Specified duration
IV	Impulse vector	SI	Specified insensitive
LMM	Lagrange multiplier method	SISO	Single-input single-output
LP	Linear programming	SMA	Simple moving average
LPF	Low-pass filter	SMC	Sliding mode controller
LQR	Linear quadratic regulator	ST	S-curve trajectory
LS	Least square	TDF	Time-delay filter
LTV	Linear time-varying	TPM	Time parameter mapping
MCTS	Monte Carlo tree search	TVIST	Time-varying input shaping technique
MII	Multiple impulse input	UMZV	Unity magnitude zero vibration
MIMO	Multi-input multi-output	WLS	Weighted least square
ML	Machine learning	ZRV	Zero residual vibration
MPC	Model predictive control	ZV	Zero vibration
MRCS	Model reference command shaping	ZVD	Zero vibration and derivative
MSE	Mean square error	ZVI	Zero vibration and minimum integral



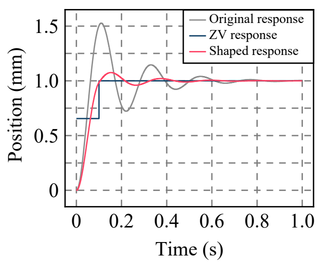
(a) A block diagram of IS control. The input command passing through the input shaper is convolved with the impulse sequence to drive the system



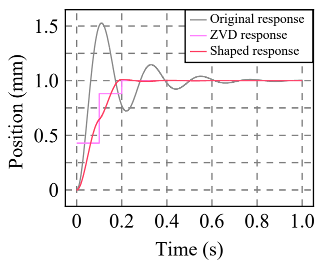
(b) The shaping process of input shaper. Notably, if the input impulse does not cause vibration, neither does the convolution



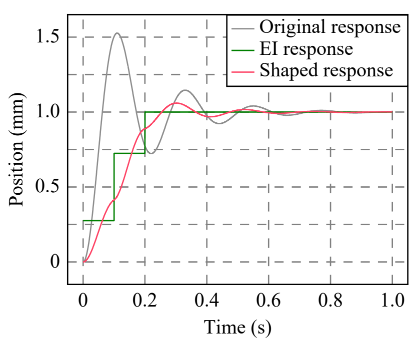
(c) Combined effect of two-impulse response. Note that the two impulses, given at time A1 and A2, respectively, have the same amplitude but opposite directions, thereby canceling each other out when superimposed



(d) The FRF curves of ZV shaper



(e) The FRF curves of ZVD shaper



(f) The FRF curves of EI shaper

Fig. 2. The basic rule and shaping process of IS. Note that (d), (e), and (f) demonstrate the FRF curves of several typical input shapers, i.e., ZV, ZVD and EI shapers, separately.

Defining $K = e^{-\zeta\pi/\sqrt{1-\zeta^2}}$, the sequence of ZV shaper can now be summarized as

$$ZV = \begin{bmatrix} A_i \\ t_i \end{bmatrix} = \begin{bmatrix} \dfrac{1}{1+K} & \dfrac{K}{1+K} \\ 0 & \dfrac{T_d}{2} \end{bmatrix} \tag{12}$$

where $T_d = 2\pi/\omega_d$ is the damped period of vibration.

b) Zero vibration and derivative (ZVD) shaper: In order to increase the robustness of the IS process, ZVD shaper constrains the differential (6), that is

$$\begin{cases} \displaystyle\sum_{i=1}^{n} A_i = 1 \\ \dfrac{\partial}{\partial\omega} V(\zeta,\omega_n) = 0. \end{cases} \tag{13}$$

Notably, ZVD shaper has zero derivative with respect to the change of vibration. To realize this constraint, it adopts three impulses to obtain the ZVD shaper

$$ZVD = \begin{bmatrix} A_i \\ t_i \end{bmatrix} = \begin{bmatrix} \dfrac{1}{C} & \dfrac{2K}{C} & \dfrac{K^2}{C} \\ 0 & \dfrac{T_d}{2} & T_d \end{bmatrix} \tag{14}$$

where $C = 1 + 2K + K^2$. Meanwhile, a ZVDD shaper can be obtained by setting the second derivative of (6), that is, the shaper can be extended indefinitely with repeated differentiation [52].

c) Extra insensitivity (EI) shaper: An EI shaper limits the residual vibration to some low, but acceptable level, and its constraints are set as

$$\begin{cases} V(\omega_n) = V_e \\ V(\omega_{n-n1}) = 0 \\ V(\omega_{n+n2}) = 0 \\ \dfrac{\partial}{\partial\omega} V(\omega)\big|_{\omega_n} = 0 \end{cases} \tag{15}$$

where V_e is the allowable limited bound of the vibrations, ω_{n-n1} and ω_{n+n2} are two frequency points near the natural frequency. In undamped or lightly damped systems, the amplitude and time delay are calculated as

$$EI = \begin{bmatrix} A_i \\ t_i \end{bmatrix} = \begin{bmatrix} \dfrac{1+V_e}{4} & \dfrac{1-V_e}{2} & \dfrac{1+V_e}{4} \\ 0 & \dfrac{T_d}{2} & T_d \end{bmatrix}. \tag{16}$$

In order to better explain the essence of IS prefiltering technology, the FRF curves of ZV, ZVD and EI shapers are shown in Fig. 2(d)−2(f), respectively.

B. Residual Vibration Control

1) Designing Steps: Considering designing methods, it can be generally categorized as response-based designing and mechanism-based designing [53]. On the one hand, the response-based method emphasizes the system's external input-output responses. It infers the system dynamic characteristics and designs controllers accordingly by observing the actual responses. Note that different systems require different types of controllers or control strategies, and adequate high-quality data is critical for effective implementation. On the other hand, the mechanism-based method basically models the system vibration as a vibration ratio function, i.e., (6). Specifically, it emphasizes a deeper understanding of the internal vibration mechanisms within the system, considering factors such as structure and material properties and employing differential equations to establish mathematical models. To obtain robustness, previous studies [54]–[56] relax the constraint and define the function as

$$V(\zeta,\omega_n)=\sqrt{C^2(\zeta,\omega_n)+S^2(\zeta,\omega_n)}. \tag{17}$$

Various constraint equations such as robustness [57], time-delay [58]−[61] and amplitude [62] have been introduced to jointly achieve the desired input shaper. In addition, the input shaper convolved with a proper filter can ensure the second-order derivability of the desired position or avoid undesirable high frequency [63].

In general, response-based method primarily relies on the external system responses, making it advantageous for more complex systems, whereas mechanism-based method involves analyzing the internal structure and is better suited for simpler systems.

2) Optimizing DDVC: Recently, research on data-driven optimizing method emerges, since the achievement of various sensors and measuring tools brings a great amount of high precision data [64]. By measuring a certain amount of actual data, the data-driven optimizing method learns the error between the ideal and actual values, and adjusts the model parameters to approximate the actual data. More specifically, optimizing DDVC can be generally summarized as artificial intelligence methods [65] and iterative methods [66], [67]. In an ideal case, the system in the desired position should stay stationary, thus, the error is the deviation of the measured speed v_i (ζ, ω_n) from the stationary condition v_{0i} = 0, and the objective function f (ζ, ω_n) is defined as

$$\arg\min_{\zeta,\omega_n} f(\zeta,\omega_n)=\arg\min_{\zeta,\omega_n}\left(\frac{1}{2}\sum_{i=1}^{n}\|v_i(\zeta,\omega_n)\|^2\right). \tag{18}$$

Note that the optimization objective is to minimize the vibration by figuring out the optimal undamped natural frequency ω_n and damping ratio ζ. Besides, in different system applications, optimization objects can be adjusted to residual vibration impulses or swing angles.

III. DDVC Methods

We present a review of state-of-the-art DDVC methods from designing to optimizing perspectives. In addition, in Tables II and III, we summarize the main characteristics of existing studies, and illustrate their structures and feature descriptions.

A. Designing Steps

1) Response-Based Designing

A response-based method analyzes the system input-output response and calculates the frequency response, step response, impulse response, and other characteristics of the system [68], thus designing the corresponding controller accordingly. As shown in Tables II(a)−II(j), the response-based methods are mainly adopted in DDVC, i.e., Feedforward control, and Feedback control.

a) Feedforward control: As shown in Table II(a) and II(b), feedforward controller proactively modifies system input to achieve better control performance by predicting its future behavior. Bruijnen and Dijk [69] introduce a filter design that integrates input shaping and feedforward filter, enabling the handling of flexible motion systems that might containing non-minimum phase behavior. Yang and Zhang [70] propose a feedforward control method for non-repetitive motion, which can obtain high performance for both repetitive and non-repetitive motion trajectories under actuator constraints. In feedforward control, the primary objective is to achieve precise tracking of a setpoint by compensating for the known system behavior [71], and the dependence of feedforward controller on system model should be removed as much as possible, while achieving high control precision and robustness [72], [73].

b) Feedback control: To achieve precise system control, feedback control adjusts the controller outputs based on the error between the system output and the desired one. Besides, in Tables II(c)−II(j), the commonly used feedback controllers include PID, LQR, PFC, GSP-PID, and ADRC. A PID controller adopts the past, current and future information of prediction error to control vibration system [74]−[78]. Moreover, Duong *et al*. [79] introduce a proportional derivative (PD) controller that equates the actuator system with the critical damping system, and establish the gain condition for the controller. Cui *et al*. [80] combine active disturbance rejection control (ADRC) with IS that realizes the fast disturbance rejection and non-overshoot set-point tracking without a precise model. Abdullah and Rossiter [81] propose potential simple modifications to conventional predictive functional control (PFC) algorithms that improve the constraint handling properties of challenging dynamics processes such as integral, underdamping, or unstable modes.

Note that various controllers may exhibit similar control architectures despite having different control mechanisms. Kocak *et al*. [82] propose an intelligent IS selection method based on fuzzy logic control (FLC), which can set optimum settling time, positioning accuracy and minimum residual vibrations. Yuan *et al*. [83] propose a vibration control strategy combining IS and sliding mode, which utilizes clonal selection algorithm combining cloud model and reverse learning (CSACCMRL) to optimize the parameters of the sliding mode controller (SMC), thus suppressing residual vibration caused by forging press impact.

2) Mechanism-Based Modeling

A mechanism-based method mainly depends on a) Residual vibration measures; b) Input command processing; c) Trajectory processing; and d) Filter combination. The structure and description of methods b)−d) are shown in Tables II(i)−II(j).

a) Residual vibration measures: These methods define new constraints or residual vibrations ratio to deal with differential equations, thus obtaining efficient input shapers. Shan *et al.* [84] propose a robust optimal input shaper (OIS) and a highly efficient index, i.e., the residual energy index (REI), to achieve quick measurements of the vibration reduction efficiency. Alghanim *et al.* [85] propose the control strategies including zero vibration and minimum integral (ZVI) and minimum vibration and integral (MVI) to provide additional

TABLE II
SUMMARY OF DESIGNING DDVC STRUCTURE

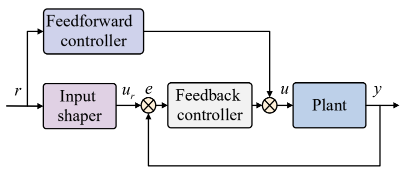
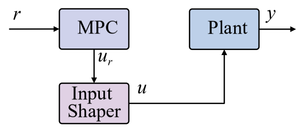
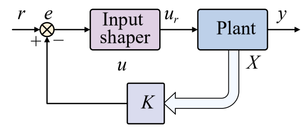
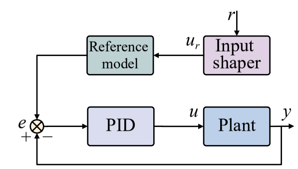
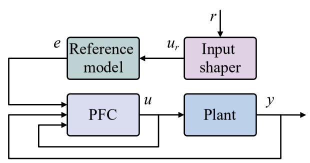
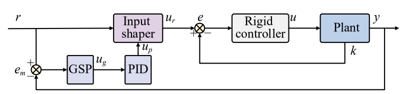
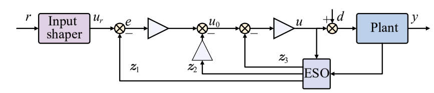
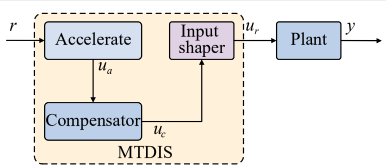
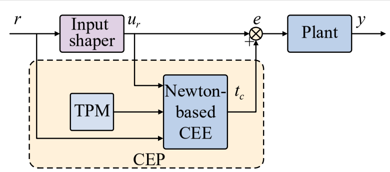
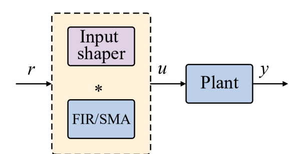
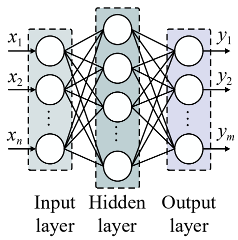
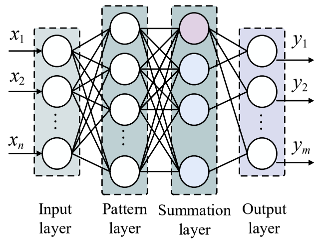
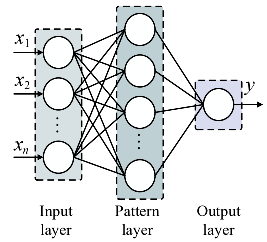
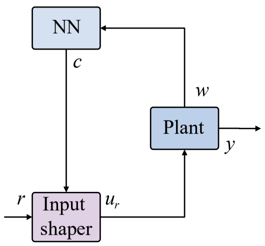
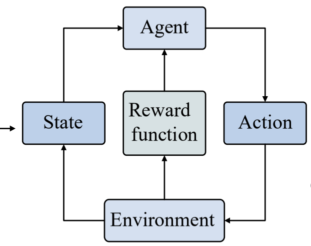
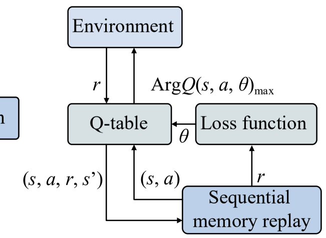
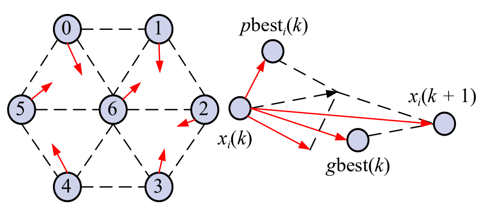
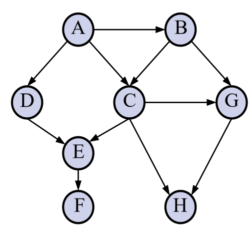
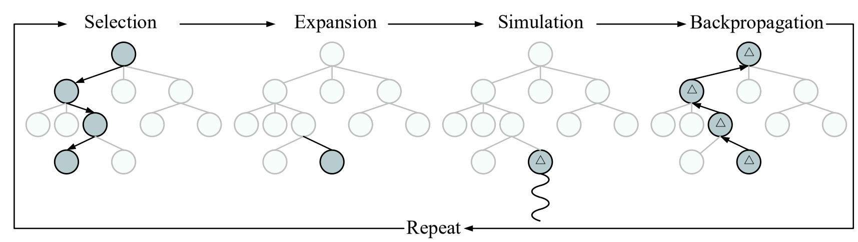
	Response-based			
	Feedforward control		**Feedback control**	
Structure	 (a) Input shaping joint feedforward (ISFF)	 (b) Model predictive control (MPC)	 (c) Linear quadratic regulator (LQR)	 (d) Proportional-integral-derivative (PID)
Description	It concurrently processes input commands with the input shaper, ensuring precise tracking of set values by compensating for the known system behavior.	It computes a control command and passes it to the input shaper for adjustment to eliminate vibration and shock in the system, thereby achieving better control performance. In addition, the GPC controller has the same structure.	It calculates the optimal state feedback controller gain matrix to influence the system output, and continuously receives feedback signals from the system to update and adjust the control commands to make the system state converge stably to the desired value.	It outputs control commands based on the error between the desired and actual output, while receiving feedback commands to update and adjust the control commands, thus keeping the system output consistent with the desired one. In addition, the PD, PI, PIPCFC, and SMC controllers have the same structure.
	Feedback Control			
Structure	 (e) Predictive functional control (PFC)	 (f) Generalized smith predictor-proportional-integral-derivative (GSP-PID)	 (g) Active disturbance rejection control (ADRC)	
Description	It improves the control performance and robustness by predicting the future behavior of the system and adjusting the control signal accordingly.	It inserts a low-pass filter, i.e., generalized smith predictor, in the feedback path to compensate for delay and receives feedback commands to update and adjust the control commands, thus improving the anti-interference performance.	It achieves real-time compensation of system disturbances by estimating the disturbances and control inputs, and continuously updates and adjusts the control signals based on feedback signals from the system to make the system's state converge stably to the desired value.	
	Mechanism-based			
	Input command processing	**Trajectory processing**	**Filter combination**	
Structure	 (h) Modified zero-time delay input shaping (MTDIS)	 (i) Contour error precompensation (CEP)	 (j) Finite impulse response/simple moving average (FIR/SMA)	
Description	It employs an acceleration block to shorten the length of the original control input, and introduces a compensation block to reduce the time delay, thus overcoming the non-smoothness issue caused by the acceleration.	It establishes a trajectory TPM and provides the reference points for contour error estimation. In addition, it uses a Newton-based TPM to find the contour error points, which reduces contour errors and avoids structural vibrations.	It uses a set of weighted coefficients to filter the input commands, thereby removing high-frequency noise and interference, and outputs the filtered commands to affect the system's output.	

TABLE III
SUMMARY OF OPTIMIZING DDVC STRUCTURE

	Artificial intelligence method					
	Neural network				Reinforcement learning	
Structure	 (a) Artificial neural network (ANN)	 (b) General regression neural network (GRNN)	 (c) Radial basis function neural network (RBFNN)	 (d) Control structure with neural network (NN)	 (e) Reinforcement learning (RL)	 (f) Q-table learning
Description	It typically involves offline training sets with optimal IS shaper parameters, taking the system state, such as joint angles and loads, as the input, and the IS parameters, such as damping ratio and natural frequency, as the output. It predicts optimal IS parameters for vibration control in uncertainty systems.	It generates kernel function and weight by clustering, uses loss function to calculate error and iteratively optimizes repeatedly, and realizes the prediction of optimal vibration control parameters through offline training sets with optimal IS shaper parameters.	It works by mapping the input data into a high-dimensional space and optimizing the output using linear regression or classification algorithms for optimal IS parameters' fitting and prediction.	It flexibly adjusts the optimal IS parameters according to the variation of the system state parameters through a well-trained NN structure.	In RL, the agents influence the environment by taking different actions and receiving feedback commands (i.e., rewards or punishments) from the environment in order to adjust their strategies to maximize long-term cumulative rewards.	The agent selects actions according to certain strategies at each time step, and updates the value of the corresponding state-action pair in the Q table according to the reward signal returned by the environment. Gradually learn optimal strategies to maximize long-term cumulative rewards.
	Iterative method					
	Evolutionary algorithm			Search algorithm		
Structure	 (g) Particle swarm optimization (PSO)		 (h) Bayesian search (BS)	 (i) Monte carlo tree search (MCTS)		
Description	It considers the optimization problem as an objective function, and represents the solutions as particles which are randomly initialized as a swarm. Besides, each particle has its own velocity and position, and iteratively searches for the optimal solution by interacting with other particles in the swarm.		It is a graphical model used to represent the dependency relationships between variables, and describe the relationships between variables using conditional probability distributions.	It builds a search tree to represent the system's state and optional actions, continuously simulates the system process to evaluate the win rate of each action. In each iteration, it expands the search tree by selecting the best action and updating the win rate information. Therefore, the optimal solution is found by minimizing the number of searches through constant iteration.		

flexibility.

b) Input command processing: The main task of input command processing is to modify the input impulse, including selecting impulse properties, impulse acceleration, and compensation. Kang [86] introduce the impulse vector (IV) and propose an equal shaping-time and magnitude (ETM) shaper that can be well applied to systems with varying natural frequencies. Li *et al.* [87] propose an input command error compensation method (ECM) to track slope commands without delay. Li *et al.* [88] introduce the positive and negative alternating impulse sequence and propose the input shaper with negative impulse input (NII) that achieve smooth transition and faster time response. Du *et al*. [89] propose a generalized input shaper with multiple impulse input (MII) to promote the anti-roll control performance of the second-order damping system.

As shown in Table II(h), the impulse acceleration and compensation processing effectively addresses the time delay. Zhao and Tomizuka [90] propose a modified zero-time delay IS (MTDIS) method, which accelerates the input command and designs the impulse compensator to suppress residual vibration of industrial robot with flexibility.

c) Trajectory processing: These methods aim to plan motion trajectory, velocity magnitude and direction to compensate trajectory error caused by IS. Zhang *et al.* [91] propose a trajectory design strategy using Cartesian coordinates to obtain the shaped trajectory, thus controlling system vibration. Zhang *et al*. [92] propose a vibration control strategy that adopts Lagrange multiplier method (LMM) to obtain the optimal impulse amplitude parameters, and uses predictive path scheduling (PPS) to reduce the system response time delay, motion control error and positioning control error caused by IS. Li *et al*. [93] propose a Cartesian trajectory planning (CTP) IS method based RLS, which shapes the normalized interpolation function of Cartesian trajectory planning.

As shown in Table II(i), trajectory processing is able to effectively compensate for contour errors. Wang *et al*. [94] propose time parameter mapping (TPM) and CEP for multi-axis IS, which uses the Newton algorithm (NA) to optimize the contour error estimation (CEE), thus reducing the structural vibration.

d) Filter combination: The most common IS methods are summarized as time-delay filter (TDF) [95] and low-pass filter (LPF) [96]. TDF is suitable for simple target system that natural frequencies and damping ratios can be easily obtained, and LPF is often combined with finite impulse response (FIR) filter to ensure finite settling time for system modes with known natural frequency and damping ratio [97]. As shown in Table II(j), the filter is mostly convolved with an input shaper. Thomsen *et al*. [98] convolve discrete time time-varying input shaping technique (TVIST) with output side algorithm FIR filter, which can be extended to higher order for additional effectiveness. Kim and Croft [99] propose the optimal S-curve trajectory (ST), robust zero-vibration (RZV) shaper and dynamic zero-vibration (DZV) shaper using simple moving average (SMA) filter to suppress a wider frequency range.

B. Optimizing DDVC Steps

1) Artificial Intelligence Method

An artificial intelligence method can effectively learn parameter variations in complex and nonlinear systems [100] and realize real-time control [101]. As shown in Tables III(a)–III(f), the commonly adopted artificial intelligence methods in DDVC mainly include a) Neural network ones; and b) Reinforcement learning ones.

a) Neural network: As shown in Table III(a), the ANN methods exhibit powerful adaptive and nonlinear learning capabilities, enabling them to learn complex mappings between system states and input shaper parameters. Rehman *et al*. [102] propose an adaptive ZVD shaper based on ANN, which realize the swing control of crane under the variation of cable length and payload mass. Zhang *et al*. [103] propose a post-adaptive zero residual vibration (ZRV) input shaper, which establishes a full connection multilayer ANN trained by multiple sets of excitation trajectory samples and adopts adaptive forgetting factor to update recursive least square (RLS) method, thus solving the issue of time cost in the case of frequent trajectory variation. Ramli *et al*. [104] propose a hybrid method of predictive NNUMZV and adaptive PID like neural network (APIDLNN) controller to realize real-time swing control of an overhead crane under simultaneous hoisting and external interference.

As shown in Tables III(b)–III(d), with the radial basis function structure, the RBFNN generally has a faster training speed while the GRNN has a better generalization ability which can help to avoid overfitting problems [105], Nithi-Uthai and Chatlatanagulchai [106] propose an RBFNN IS reference model matching backstepping controller (RMMBC), which compensates the uncertainty and disturbance of the system.

b) Reinforcement learning: As shown in Tables III(e) and III(f), Reinforcement learning (RL) is a typical discrete behavior learning model, which conducts multiple interactive learning between the agent and the dynamic environment without any pre-existing knowledge and makes appropriate choices to obtain rewards, thus achieving optimal solution. Xu *et al*. [107] propose an RL based control method for specified insensitive (SI) input shaper, which utilizes the RL agent to find the maximum reward function, i.e., the optimal parameter with minimum vibration amplitude, thus achieving better vibration control effect and robustness. Zhang *et al*. [108] propose a deep reinforcement learning-based optimization method for input shaping (RLIS), which increases the learning efficiency and simplifies the design process through a selection mechanism based on state value and a fuzzy reward system.

2) Iterative Method

a) Least squares problem: The least square (LS) method is an efficient and scalable optimization method for identifying system parameters [109]. Yin *et al*. [110] propose a hybrid feedforward force/position control strategy that applies multi-mode adaptive IS and uses weighted least square (WLS) method to identify shaper parameters. Zou *et al.* [111] introduce a learning exponential jerk trajectory planning, which dynamically adjusts the parameters of exponential filter in real-time using an iterative learning strategy designed by gradient descent (GD) principle, thereby maximizing the effectiveness of vibration suppression. Zhang *et al.* [112] propose an optimal arbitrary time-delay filter (OATF), which apply an iterative learning scheme based on the secant method and WLS to obtain a better natural frequency estimate.

b) Evolutionary algorithm: As shown in Table III(g), the evolutionary algorithm, represented by PSO, involves individuals searching for optimal solutions by iteratively updating their own positions and velocities as well as the position and velocity of the global optimal solution. Jallouli-Khlif *et al.* [113] propose a composite control law based on the IS approach and a fractional proportional integral controller, which is tuned by ant colony optimization (ACO) algorithm and reduces the settling time and vibrations of the system. Li *et al*. [114] propose a PSO algorithm based on RLS finite search space (RLS-PSO), which identifies the dynamic parameter and uses the results to design a coupled ZVD shaper, suppressing residual system vibration with a higher accuracy and convergence speed. The self-tuning capability of the evolutionary algorithm can effectively deal with the issue of IS tuning in black boxes, systems with nonlinear, and more complex plants [115].

c) Search algorithm: As shown in Tables III(h) and III(i), The search algorithms use strategies, i.e., probability, and search tree structures, to iteratively adjust the solutions in the search space, thereby finding the optimal solution. Jia *et al.* [116] present a parameter learning strategy for two impulse input shaper that adjusts offline parameters by extrapolation interpolation algorithm and golden section search (GSS) through vibration amplitude measurement. Patel and Wearer [117] propose a minimum time control algorithm (MTCA) that applies Monte Carlo tree search (MCTS) method to find the optimal control strategy for the input shaper. Pásztori *et al*. [118] apply Bayesian search (BS) algorithm considering the previous Gaussian Process as a prior distribution to select the optimal input shaper parameters.

C. Summary

We present a holistic overview of the progress in DDVC from the designing to optimizing perspectives, where the state-of-the-art is comprehensively reviewed and categorized. Besides, the main characteristics and classification of existing designing and optimizing methods are summarized in Tables IV and V, including their tasks and applications.

Considering the limitations of existing DDVC methods:

1) They mostly focus on advancing either the designing or optimizing processes separately, neglecting the potential benefits of concurrently improving both processes, which is worth further investigation.

2) Existing optimizing DDVC methods mainly utilize simple neural network or basic artificial intelligence techniques, and are limited to validation on other experimental equipment and environment, lacking sufficient generality [119], [120]. Considering this aspect, it is urgent to explore advanced artificial intelligence techniques to enhance the adaptability of DDVC methods to various systems and vibration modes. In addition, there is currently no standardized publicly available dataset to validate various state-of-the-art DDVC methods.

IV. Metrics

This section summarizes the DDVC-related metrics, including 1) Commonly-adapted evaluation metrics for a DDVC model; and 2) Control metrics used to compare different DDVC methods.

A. Evaluation Metrics

In the realm of DDVC models, evaluation metrics serve as essential tools for gauging the performance and accuracy of models in predicting outcomes. These metrics encompass a range of measures, including but not limited to root mean square error (RMSE), mean square error (MSE), and coefficient of determination (R^2) [121], offering quantitative insights into algorithmic performance within a given dataset. Besides, they provide a more comprehensive insight into the model's effectiveness in data-driven tasks, facilitating the model optimization and the enhancement of prediction accuracy. In Table VI, several commonly used evaluation metrics in DDVC models are summarized.

B. Control Metrics

Table VII outlines the control metrics in the DDVC methods, which serve as the foundation for a comprehensive assessment of system performance, and encompass parameters like settling time, transient response time, and robustness [122], etc. Additionally, a thorough evaluation of these control metrics enables a more detailed understanding and comparison of the performance among different vibration control methods, offering robust support for system optimization and design decisions.

V. DDVC in Engineering and Future Development

A. DDVC in Engineering

DDVC is a versatile method with a broad range of potential applications in various engineering, the detailed characteristics and the corresponding specific DDVC methods are presented in Table VIII, and some engineering scenarios are as follow:

1) Robot Control: DDVC can be used in various aspects of robot control, such as position control, velocity control, and force control [123]. Chen *et al.* [124] utilize the finite element method and the IS technique to improve the performance and reliability of mechatronics systems. Thomsen *et al*. [125] apply the TVIST on UR robots to achieve more precise motion control. Sahoo and Singhose [126] utilize the IS to reduce impact loads during collisions of flexible robots, thereby improving the reliability and durability of the system. In conclusion, DDVC has shown significant advantages in promoting the control performance of robots in various aspects.

2) Pendulum Control: Collectively, DDVC methods are widely adopted to control pendulum system, i.e., Flexible beam [127]−[129], underactuated system [130], and Boom system [131]. Kim *et al*. [132] present a detailed modeling analysis of

TABLE IV
SUMMARY OF DESIGNING DDVC

Ref.	Year	DDVC method	Shaper	Task	Experimental setup
[69]	2012	ISFF, SISO	–	Combine IS and classical feedforward to improve tracking accuracy	6 2-DOF forcers and a 6-DOF interferometer sensing system
[70]	2022	DFPOMC	–	Provide optimal trajectory tracking performance under actuator constraints and robustness to non-repetitive trajectories	Servo motor platform
[71]	2014	ISFF	–	Enhance the system's performance in executing point-to-point reference trajectories	Prototype industrial motion system
[72]	2014	SISO, MIMO, FIR	–	Realize zero error tracking and reduce stabilization time in dynamic systems	Simulation of wafer scanning
[73]	2018	MPC	ZV	Control the payload oscillations effectively under the influence of model parameter error and nonlinearity	Simple pendulum connected to a sliding cart
[74]	2023	PID	ZVD	Suppressing the angle swing using a designed composite control framework	Two-dimensional model of overhead crane
[75]	2021	PID, LP, QP	–	Constrain internal control signals and system output within a certain range	Mass-spring-damper system
[76]	2022	PID, SMC, FLC	ZV, ZVD, ZVDD	Track the ideal trajectory and suppressing payload sway, unaffected by ship motion	Simulation of a five degree-of-freedom shipboard gantry crane
[77]	2020	PID, PSO	–	Achieve the best possible performance for both objectives with a dual mode control system	Arduino based temperature control kit prototype
[78]	2018	PID, PSO	ZV	Trigger both the identification and retuning procedure using the error derivative among the model and system output	Simulation system
[48]	2021	GSP-PID	–	Improve control bandwidth and disturbance rejection	6 DOF industrial robot
[49]	2022	PD	ZV	Control point-to-point motion of the gantry crane	Gantry crane
[79]	2022	PD	ZV, ZVD	Suppress the vibration of flexible dynamic systems	Overhead crane
[50]	2019	PD	ZV, ZVD	Suppress the flexible manipulator vibration caused by external disturbance or working	Flexible manipulator experimental platform
[80]	2018	ADRC	ZV	Improve the response capability and anti-interference performance of ADRC	Simulation system
[51]	2018	PFC	ZV	Suppress vibration and control precise position of minimally invasive surgical robot during intraoperative operation	Laparoscopic minimally invasive surgical robotic manipulator
[81]	2018	PFC	–	Solve the issues of unstable poles, vibration modes, or integrated modes in dynamic systems	Quanser SRV02 servo-based unit
[52]	2019	FLC	Two-mode ZV-ZV	Control position and suppress vibration of a flexible solar panel drive system	Flexible solar array drive system
[82]	2022	FLC	–	Optimize the positioning accuracy and minimum residual vibration of the robot system	Quanser flexible link
[53]	2019	PIPOFC	ZV	Suppress vibrations of the cart payload with external disturbance	Cart and pendulum model
[83]	2022	CSACCMRL, SMC	ZVD	Reduce the residual vibration of forging robot	Forging robot simulation model
[54]	2018	LQR	ZV	Minimize command-induced vibration while allowing energy-efficient point-to-point motion	Simulation of a two-link flexible-arm manipulator
[84]	2022	REI	OIS	Suppress the vibration of high-speed pick-and-place parallel robot	4-DOF SCARA-type parallel robot
[85]	2019	ZVI, MVI	ZV, ZVD	Minimize the system sensitivity to crane cable-length variations	Overhead crane model

TABLE IV
SUMMARY OF DESIGNING DDVC (CONTINUED)

Ref.	Year	DDVC method	Shaper	Task	Experimental setup
[55]	2022	IV	SD, ZV, ZVD	Suppress residual vibrations of the vibratory system at the specified shaping times with a proposed SD shaper	Flexible horizontal cantilever beam
[56]	2020	IV	ZV, ZVD	Validate the performance in view of robustness to modeling errors of the proposed generalized ZVD shaper	Up-and-down flexible beam
[86]	2019	IV	ZVD, ETM	Introduce impulse vectors and design a new class of input shapers.	Flexible beams with laser Sensors
[87]	2019	ECM	–	Address the time delay problem introduced by shaper during vibration control	RB03A1 6-DOF industrial robot
[57]	2020	NII	NHMMIS	Reduce the residual vibration of a 3-DOF robot	Mathematica simulation
[88]	2021	NII	ZV, ZVD	Optimize vibration suppression for the transition process of grinding and polishing	MATLAB simulation
[58]	2019	NII	NHMMIS	Suppress the vibration when the amplitude and bandwidth of the modes differ significantly	3 DOF parallel robot
[59]	2020	MII	ZV, ZVD, NZV	Provide better swing angle control performance and shorter operation time with the proposed NZV shaper	Simulation model of a trolley grab system.
[89]	2018	MII	–	Control the crane swing in industrial environment	MATLAB simulation
[60]	2019	ST	ZV	Solve the problem of high dependence on modal parameters and time delay of input shapers	J4 and J5 axes of a 6 DOF industrial robot
[61]	2018	ST	ZV	Suppress vibrations of glass substrate transfer robot	SR99H5N0041 glass substrate transfer robot
[90]	2017	MTDIS	ZV	Solve the issue of time delay and non-smooth motion of IS	FANUC M16iB industrial robot
[91]	2020	CTP	ZV	Suppress the vibration of the 2-DOF manipulator during operation	Mechanical arm with 2 DOF
[92]	2018	PPS, LMM	ZVDD	Suppress the residual vibration of industrial robot end-effector	6 DOF robot j5 axis experiment platform
[93]	2021	CTP, RLS	ZVD	Suppress the robot end vibration caused by the flexible transmission parts	6 DOF industrial robot
[94]	2022	CEP	Multi-axis ZVD	Simultaneously reduce the contour error and avoid structural vibration by precompensating the shaped trajectory	Industrial biaxial mechatronic motion system
[98]	2019	FIR	TVIST, ZV, ZVD, ZVDD	Reduce mechanical vibrations in industrial robots with position control and feed-forward torque	Simulation system
[62]	2023	FIR	ZVD	Suppress those frequency components that generate vibrations in rotating systems	Reduced carousel model
[63]	2021	LTV-FIR, PID, PD	ZVD	Reduce the effect of model error with model reference feedback and achieve fast point-to-point motion without steady-state errors	X-Y micro-positioning stage
[99]	2018	SMA, ST	ZV, RZV, DZV	Suppress vibration of multi-degree of freedom industrial robots	6 DOF industrial robot

TABLE V
SUMMARY OF OPTIMIZING DDVC

Ref.	Year	DDVC method	Shaper	Task	Experimental setup
[97]	2020	Extended ANN	ZVD	Suppress the residual vibrations in high-speed motions under varying payload masses and poses	Staubli RX90CR robot
[102]	2022	ANN	ZVD, ZVDD	Control payload swing of a tower crane under varying cable lengths and payload masses	Laboratory tower crane
[64]	2020	ANN	ZVD, EI	Suppress the payload oscillation of a tower crane	Laboratory tower crane
[65]	2020	ANN	–	Reduce the vibration and avoid noise of the feedback sensor signals	Over crane control system
[67]	2021	ML	ZD, ZVDD	Solve the multi-link flexible link manipulators vibration problem	Simscape-multibody platform
[121]	2023	ANN, PID	UMZV, ZVDDD	Consider the system nonlinear characteristics and suppress the system vibration	2-D overhead crane with distributed-mass beams
[68]	2023	ANN	ZVD, EI	Achieve a satisfactory damping performance under an obstacle avoidance scenario	Laboratory tower crane
[104]	2020	NNUMZV, APIDLNN	UMZV	Control the vibrations of a crane despite payload hoisting and external disturbance	Overhead Crane
[100]	2020	RBFNN, PID	ZV	Compensate the sudden force caused by the myospasm	Simulation system
[106]	2019	RBFNN, RMMBC	–	Optimize backstepping to control the vibration of rigid-flexible system	One link Flexible Joint Robot manipulator
[108]	2022	RLIS	ZV	Reduce the dependence on the acceleration signal and avoid the complex vibration mode identification	SCARA robot with four degrees of freedom
[107]	2020	RL	SI	Suppress the vibration of picking robot in moving process	Double pendulum model
[101]	2018	RL	ZV, SI	Minimize unwanted residual vibration of flexible machines	Simulation system
[103]	2021	ANN, RLS	ZRV	Suppress the residual vibration of multi-axis servo system caused by the system flexibility in the emergency stop section of high-speed motion	Multi-axis servo drive platform and a real time control system based on EtherCAT Fieldbus
[110]	2022	WLS	ZV	Reduce the trajectory tracking error and suppress the robot end residual vibration	RB03A1 6-DOF industrial robot
[112]	2019	WLS	OATF	Address the nonlinear and time-varying residual vibration problem in robot	GSK-RB03A1 6-DOF industrial robot
[66]	2019	RLS, EKF	ZV, ZVD, EI	Mitigate vibrations in nonlinear systems	Simulation system
[111]	2023	GD	ZV, ZVD	suppress the residual vibrations of industrial robots with a learning exponential jerk trajectory planning	SCARA robot experiment platform
[131]	2020	PSO	ZV, ZVD	Provide a cost-effective and safe method for transferring the payload under simultaneous radial and tangential motion of the tower crane	3-DOF laboratory tower crane
[96]	2019	PSO	UMZV	Reduce payload sway of an underactuated 3D overhead crane with hoisting effects	3D laboratory overhead crane
[122]	2021	PSO	ZV, ZVD	Suppress the vibration during the payload transportation process	Laboratory size crane
[114]	2023	PSO, RLS, GA	ZVD	Reduce residual vibration of the ball screw drive system during emergency stop during high-speed movement	Ball-screw drive system
[115]	2023	GA	–	Solve the nonlinear vibration problem of large swing angle and non-zero initial conditions	Overhead crane systems
[113]	2021	ACO, PI	ZV	Promote the accurate positioning of the prosthetic hand, reduce the stability time of the system, and suppress system vibration	Simulation system of the prosthetic hand
[116]	2018	GSS	Two-mode IS	Minimize residual vibration amplitude without an exact model	Single joint manipulator with flexible joint
[117]	2020	MCTS, MTCA	–	A 3-stage boost converter-based system feeding a load	Paralleled DC-DC converters
[123]	2023	RRT, PD	ZVD	Reduce the vibrations of flexible appendages caused by the trajectory tracking for each spacecraft	Simulation of a flexible spacecraft
[118]	2020	BS	ZV	Reduce vibration in complex underactuated robots	Mobile robot base and a flexible beam camera system

TABLE VI
SUMMARY OF EVALUATION METRICS

Evaluation metrics	Equation & Description
δ_i	$\delta_i = \frac{\lvert t_i - \hat{t}_i \rvert}{t_i}$. The absolute error ratio [44].
PA	$PA = 100\% - \frac{1}{n}\sum_{i=1}^{n}\frac{\lvert t_i - \hat{t}_i \rvert}{t_i} \times 100\%$. The prediction accuracy [44].
RMSE	$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(t_i - \hat{t}_i)^2}$. The root mean square error [121].
R^2	$R^2 = 1 - \frac{\sum_{i=1}^{n}(t_i - \hat{t}_i)^2}{\sum_{i=1}^{n}(t_i - T)^2}$. The coefficient of determination [121].
MSE	$MSE = \frac{1}{n}\sum_{i=1}^{n}(t_i - \hat{t}_i)^2$. The mean square error [104].
MTS	$MTS = \max\{\lvert A(t_i)\rvert\}$. The maximum transient swing [108].
IAE	$IAE = \int_0^{\infty}\lvert t_i - \hat{t}_i \rvert dt$. The integral absolute error [96].
RAE	$RAE = \frac{\sum_{i=1}^{n}\lvert t_i - \hat{t}_i \rvert}{\sum_{i=1}^{n}\lvert t_i - T \rvert}$. The relative absolute errors [114].

Where $i = 1, 2, \ldots, n$, and n denotes the number of the samples, y_i and $\hat{y}_i$ denote the actual and estimated value of residual vibration respectively, and T is the average of the measured values.

TABLE VII
SUMMARY OF CONTROL METRICS

Control metrics	Equation & Description
Transient response time	– The time required for the system to reach steady state from disturbance or instruction change [36].
Steady state vibrations	– The amplitude and frequency of the output commands periodically fluctuate within a certain range and tend to stabilize after the transient response time [36].
Robustness	– Robustness is used to evaluate the ability of input shapers to resist external interference such as uncertainty, disturbance, and noise [36].
Settling time	– The time required for the system to reach and maintain within a given error band in its motion direction after disturbance or change in instruction [113].
L1 control effort	$L1$ control effort $= \int_0^{\infty}\lvert u(t)\rvert dt$. The time integral of the absolute value of the control signal [105].
L2 control effort	$L2$ control effort $= \int_0^{\infty}u^2(t)dt$. The time integral of the square of the control command [105].
H_∞ control effort	– A controller to minimize the system H-infinity norm to achieve optimal control [105].

where $u(t)$ denotes the control command.

TABLE VIII
SUMMARY OF DDVC IN ENGINEERING

Application	Characteristics & Specific DDVC
 (a) Robot control	a) Each axis exhibits similar vibration characteristics; b) Each axis has different vibration frequency in different positions; and c) Uncertain system modal parameters. It requires adaptive IS control methods and optimization methods for identifying system parameters, e.g., OATF [112], RLIS [108], BS [118], GA [115], WLS [110], [112], etc.
 (b) Pendulum control	a) The system parameters are uncertain but fluctuate within a certain range; and b) Rapid transportation and less expense require fast maneuverability. It requires IS methods that can perform effectively within specific system parameter ranges, e.g., SI [101].
 (c) Crane control	a) The system is actuated with finite actuation states; and b) Variations in payloads and cable lengths induce changes in the system's natural frequency and damping ratio. It requires artificial intelligence optimization methods that can learn and adjust IS parameters online, e.g., ANN, [64], [65], APIDLNN [104], RBFNN [100], etc.
 (d) Aviation control	a) Lightweight damping structure; b) Unavoidable transient vibration and elastic deformation; and c) External disturbances during motion bring about inertial uncertainty. It typically requires IS methods that combine fuzzy theory control, e.g., FLC [65], etc.

the flexible beam for IS control. Cao *et al.* [133] apply the IS method to the servo motor and swing arm, and compare the effects of three input shaper ZV, ZVD and EI. In general, DDVC is typically employed to mitigate the issues of vibration and impact in pendulum control, which may arise from the nonlinear dynamics or external disturbances [134]–[139].

3) Crane Control: In crane control, DDVC is commonly used to shape the acceleration or angular acceleration resulting in control commands that are tailored to the system dynamic characteristics, e.g., tower crane [140], bridge crane [141], and overhead crane [142]. Montonen *et al.* [143] investigate the application of tower crane slewing control from the perspective of reducing load vibrations. Peláez *et al.* [144] implement the IS to address real-time control issues of multibody vibration system on a suspended double-link gantry crane. Bhayadia *et al.* [145] utilize IS to generate travelling wave motion and investigate its application in mechanical systems, particularly in suspended gantry cranes.

4) Aviation Control: After being deployed in orbit, a spacecraft can be considered as a main body with a flexible attachment which suffers from large span, low stiffness, and weak damping issues [146]−[149]. Zhu *et al* [150] apply DDVC method to suppress spacecraft vibration excitation during attitude adjustment. To enhance its control performance and stability, DDVC methods are commonly applied to the attitude control, velocity control, and position control [151]. Jia and Shan [152] propose a control strategy combining IS and variable-speed control moment gyros to suppress the flexible vibration of gyro elastic spacecraft.

B. Future Development Trends

Based on the above method summary and literature review, this section discusses the future development trends of DDVC.

1) Hard Real-Time DDVC: As shown in Fig. 2(c), IS methods inevitably suffer from time delay issues. On the other hand, the practical engineering tasks mostly deal with dynamic and varying systems [153]−[155]. Therefore, it is worth exploring more efficient and intelligent DDVC methods to respond to system changes and interferences, thus meeting the real-time and adaptive control requirements of different systems.

2) Remote Control DDVC: Notably, existing vibration control methods are limited to on-site control, while DDVC methods can utilize technologies, i.e., cloud computing and remote access to achieve remote control [156]−[160]. Particularly, equipped with high-performance computing and large-scale storage resources, DDVC methods can transfer the control tasks from on-site to remote servers, which will provide more possibilities for industrial automation and intelligent control.

3) Networked Control-Based DDVC: Currently, the rapid development of the Internet of Things and distributed control is driving the networked control-based DDVC as a significant direction in control fields. By distributing control tasks across various computing nodes for collaborative processing, it leverages abundant network and computing resources to achieve more efficient and precise command processing and control [161], which will bring promising prospects for the fields such as smart manufacturing, intelligent transportation, and industrial automation.

C. Intractable Problems and Difficulties

Despite the continuous advancements in DDVC methods, there are still some intractable problems and difficulties that require ongoing refinement.

1) Idealized Scenario: Although composite filters offer notable enhancements compared to linear or nonlinear filters, their effectiveness may be constrained in certain specific real scenarios, i.e., high angular speed of rotation. Besides, the common practice idealistically considers only the system's first-order natural frequency for shaper design, even though it's effective in suppressing most vibrations. Obtaining additional actual vibrational modes remains key to enhancing suppression effectiveness.

2) Online Real-Time: The current methods for achieving real-time DDVC entail offline learning preceding online updates, thus, an online learning method is worth developing and high demands on data and algorithms will be new difficulties. Furthermore, existing real-time updates exclusively account for changes in cable length and load, overlooking the intricate and diverse factors inherent in real-world scenarios. It's crucial to consider these factors to enhance overall robustness.

3) Poor Portability: The widespread application of DDVC methods in engineering not only enhances system efficiency but also brings forth new challenges that need to be addressed. For instance, the coordinated application of a positioning robot and a manipulator poses a challenge in determining the natural frequency, particularly due to their frequent interaction with payloads of varying geometries and weights.

4) Universally Applicable DDVC: Present research has solely focused on assessing the performance of specific input shapers, neglecting the standard of selecting the appropriate input shaper for specific systems. Consequently, formulating a comprehensive set of criteria for shaper selection is an intriguing proposition. Furthermore, it is challenging yet worthwhile for us to explore a universally applicable shaper for all systems with the assistance of data-driven methods.

VI. Conclusions

As industrial applications move towards automation and higher precision, DDVC has received more attention. Compared to traditional vibration control methods, DDVC overcomes their limitations in dealing with complex and time-varying systems, as well as non-periodic impulses, etc. This paper presents a comprehensive review of the latest research progress in DDVC methods, from designing to optimizing. We first introduce the IS theory and fundamental rules, and then provide detailed discussions of DDVC methods involved in the designing and optimizing processes, where the state-of-the-art is comprehensively reviewed and categorized. Afterwards, a summary of typical evaluation and control metrics is presented. Ultimately, practical applications in engineering and potential future research directions are summarized. In the future work, in addition to researching more advanced DDVC methods, we will also focus on establishing high-quality, publicly available datasets that can serve as a benchmark for researchers to validate the effectiveness of their algorithms. We hope that this comprehensive review can encourage researchers and engineers to perform further research on DDVC and its applications, thereby benefitting the industry.

References

[1] X.-J. Li and X.-Y. Shen, "A data-driven attack detection approach for DC servo motor systems based on mixed optimization strategy," *IEEE Trans. Ind. Inf.*, vol. 16, no. 9, pp. 5806–5813, Sep. 2020.

[2] A. Wahrburg, J. Jurvanen, M. Niemelä, and M. Holmberg, "Input shaping for non-zero initial conditions and arbitrary input signals with an application to overhead crane control," in *Proc. IEEE 17th Int. Conf. Advanced Motion Control*, Padova, Italy, 2022, pp. 36–41.

[3] H. Wu, X. Luo, and M. C. Zhou, "Advancing non-negative latent factorization of tensors with diversified regularization schemes," *IEEE Trans. Serv. Comput.*, vol. 15, no. 3, pp. 1334–1344, May–Jun. 2022.

[4] V. D. La and K. T. Nguyen, "Combination of input shaping and radial spring-damper to reduce tridirectional vibration of crane payload," *Mech. Syst. Signal Process.*, vol. 116, pp. 310–321, Feb. 2019.

[5] A. Villalonga, G. Beruvides, F. Castaño, and R. E. Haber, "Cloud-

based industrial cyber-physical system for data-driven reasoning: A review and use case on an Industry 4.0 pilot line," *IEEE Trans. Ind. Inf.*, vol. 16, no. 9, pp. 5975–5984, Sep. , 2020.

[6] M. Sun and D. Liu, "Two-loop control of harvesting mechanical arm base on adaptive input shaping algorithm," in *Proc. Int. Conf. Virtual Reality, Human-Computer Interaction and Artificial Intelligence*, Changsha, China, 2022, pp. 182–188.

[7] A. Mohammed, K. Alghanim, and M. T. Andani, "An adjustable zero vibration input shaping control scheme for overhead crane systems," *Shock Vib.*, vol. 2020, p. 7879839, May 2020.

[8] D. K. Thomsen, R. Søe-Knudsen, O. Balling, and X. Zhang, "Vibration control of industrial robot arms by multi-mode time-varying input shaping," *Mech. Mach. Theory*, vol. 155, p. 104072, Jan. 2021.

[9] Y. Song, W. He, X. He, and Z. Han, "Vibration control of a high-rise building structure: Theory and experiment," *IEEE/CAA J. Autom. Sinica*, vol. 8, no. 4, pp. 866–875, Apr. 2021.

[10] Z.-S. Ma, X. Li, M.-X. He, S. Jia, Q. Yin, and Q. Ding, "Recent advances in data-driven dynamics and control," *Int. J. Dyn. Control*, vol. 8, no. 4, pp. 1200–1221, Aug. 2020.

[11] Z.-C. Qin and Y. Xin, "Data-driven H_∞ vibration control design and verification for an active suspension system with unknown pseudo-drift dynamics," *Commun. Nonlinear Sci. Numer. Simul.*, vol. 125, no. 1, p. 107397, Oct. 2023.

[12] H. Liu, C. Zhao, X. Huang, and G. Yao, "Data-driven modeling for the dynamic behavior of nonlinear vibratory systems," *Nonlinear Dyn.*, vol. 111, no. 12, pp. 10809–10834, Apr. 2023.

[13] M. Azimi, A. D. Eslamlou, and G. Pekcan, "Data-driven structural health monitoring and damage detection through deep learning: State-of-the-art review," *Sensors*, vol. 20, no. 10, p. 2778, May 2020.

[14] Y. Zhang, S. Li, J. Weng, and B. Liao, "GNN model for time-varying matrix inversion with robust finite-time convergence," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 35, no. 1, pp. 559–569, Jan. 2024.

[15] P. Tacx and T. Oomen, "Comparing multivariable uncertain model structures for data-driven robust control: Visualization and application to a continuously variable transmission," *Int. J. Robust Nonlinear Control*, vol. 33, no. 16, pp. 9636–9664, Nov. 2023.

[16] W. Yang, S. Li, Z. Li, and X. Luo, "Highly accurate manipulator calibration via extended Kalman filter-incorporated residual neural network," *IEEE Trans. Ind. Inf.*, vol. 19, no. 11, pp. 10831–10841, Nov. 2023.

[17] L. Liu, S. Tian, D. Xue, T. Zhang, and Y. Chen, "Industrial feedforward control technology: A review," *J. Intell. Manuf.*, vol. 30, no. 8, pp. 2819–2833, Dec. 2019.

[18] S. Engelberg, "Input shaping: A tutorial introduction [lecture notes]," *IEEE Control Syst. Mag.*, vol. 41, no. 2, pp. 45–51, Apr. 2021.

[19] D.-X. Liu, J.-C. Zhang, Y. Li, and J.-J. Fang, "Research on adaptive input shaping control of fruits and vegetable harvesting robot arm," *Control Theory Appl.*, vol. 39, no. 6, pp. 1043–1050, Jun. 2022.

[20] A. Kobilov and S. W. Hong, "Delay-time adjustable input shaping method for positioning systems subject to repetitive motion," *J. Korean Soc. Precis. Eng.*, vol. 37, no. 1, pp. 25–34, Jan. 2020.

[21] A. H. Khan, X. Cao, S. Li, V. N. Katsikis, and L. Liao, "BAS-ADAM: An ADAM based approach to improve the performance of beetle antennae search optimizer," *IEEE/CAA J. Autom. Sinica*, vol. 7, no. 2, pp. 461–471, Mar. 2020.

[22] Y. Zhou, X. Luo, and M. C. Zhou, "Cryptocurrency transaction network embedding from static and dynamic perspectives: An overview," *IEEE/CAA J. Autom. Sinica*, vol. 10, no. 5, pp. 1105–1121, May 2023.

[23] M. O. T. Cole and P. Kuresangsai, "Convolution-based input shaping for finite-time settling in non-LTI systems: An LTV approach," in *Proc. IEEE Conf. Control Technology and Applications*, Hong Kong, China, 2019, pp. 964–969.

[24] A. A. M. Awi, S. S. N. N. Zawawi, L. Ramli, and I. M. Lazim, "Robust input shaping for swing control of an overhead crane," in *Proc. 22nd Asia Simulation Conf.*, Langkawi, Malaysia, 2023, pp. 180–187.

[25] S. W. Hwang, D. H. Kim, J. Park, and J. H. Park, "Equilibrium configuration analysis and equilibrium-based trajectory generation method for under-constrained cable-driven parallel robot," *IEEE Access*, vol. 10, pp. 112134–112149, Oct. 2022.

[26] Y. Shi, W. Sheng, S. Li, B. Li, and X. Sun, "Neurodynamics for equality-constrained time-variant nonlinear optimization using discretization," *IEEE Trans. Ind. Inf.*, vol. 20, no. 2, pp. 2354–2364, Feb. 2024.

[27] M. Kasprowiak, A. Parus, and M. Hoffmann, "Vibration suppression with use of input shaping control in machining," *Sensors*, vol. 22, no. 6, p. 2186, Mar. 2022.

[28] S. W. Hwang, J.-H. Bak, J. Yoon, and J. H. Park, "Oscillation reduction and frequency analysis of under-constrained cable-driven parallel robot with three cables," *Robotica*, vol. 38, no. 3, pp. 375–395, Mar. 2020.

[29] Z. Li, S. Li, and X. Luo, "An overview of calibration technology of industrial robots," *IEEE/CAA J. Autom. Sinica*, vol. 8, no. 1, pp. 23–36, Jan. 2021.

[30] R. Rehammar and S. Gasparinetti, "Low-pass filter with ultrawide stopband for quantum computing applications," *IEEE Trans. Microwave Theory Tech.*, vol. 71, no. 7, pp. 3075–3080, Jul. 2023.

[31] L. Chen, H. Zhu, R. Gómez-García, and X. Zhu, "Miniaturized on-chip notch filter with sharp selectivity and >35-dB attenuation in 0.13-μm bulk CMOS technology," *IEEE Electron Device Lett.*, vol. 43, no. 8, pp. 1175–1178, Aug. 2022.

[32] S. Fujii and Q.-C. Pham, "Realtime trajectory smoothing with neural nets," in *Proc. Int. Conf. Robotics and Automation*, Philadelphia, USA, 2022, pp. 7248–7254.

[33] Y. Liu and Z. Yang, "Trajectory smoothing algorithm based on Kalman filter," in *Proc. 7th Int. Conf. Machine Vision and Information Technology*, Xiamen, China, 2023, pp. 52–56.

[34] D. Zhu, Y. He, X. Yu, and F. Li, "Trajectory smoothing planning of delta parallel robot combining Cartesian and joint space," *Mathematics*, vol. 11, no. 21, p. 4509, Nov. 2023.

[35] R. Piedrafita, D. Comín, and J. R. Beltrán, "Simulink.® implementation and industrial test of Input Shaping techniques," *Control Eng. Practice*, vol. 79, pp. 1–21, Oct. 2018.

[36] H. Ghorbani, K. Alipour, B. Tarvirdizadeh, and A. Hadi, "Comparison of various input shaping methods in rest-to-rest motion of the end-effecter of a rigid-flexible robotic system with large deformations capability," *Mech. Syst. Signal Process.*, vol. 118, pp. 584–602, Mar. 2019.

[37] H. H. Bilgic, C. Conker, and H. Yavuz, "Fuzzy logic-based decision support system for selection of optimum input shaping techniques in point-to-point motion systems," *Proc. Inst. Mech. Eng. Part I: J. Syst. Control Eng.*, vol. 235, no. 6, pp. 795–808, Jul. 2021.

[38] H. Yavuz and S. Beller, "An intelligent serial connected hybrid control method for gantry cranes," *Mech. Syst. Signal Process.*, vol. 146, p. 107011, Jan. 2021.

[39] Y. Zhang and S. Li, "Kinematic control of serial manipulators under false data injection attack," *IEEE/CAA J. Autom. Sinica*, vol. 10, no. 4, pp. 1009–1019, Apr. 2023.

[40] P. Zhao, Y. Zhou, and R. Zhou, "A new trajectory optimizing method using input shaping principles," *Shock Vib.*, vol. 2018, p. 4173253, Sep. 2018.

[41] A. Mohammed, K. Alghanim, and M. T. Andani, "A robust input shaper for trajectory control of overhead cranes with non-zero initial states," *Int. J. Dyn. Control*, vol. 9, no. 1, pp. 230–239, Mar. 2021.

[42] T. Yi, Q. Pei, D. Li, S. Wei, D. Jia, and H. Zhang, "Optimization of simulation parameters of input shaper based on genetic algorithm," in *Proc. 2nd Int. Conf. Advanced Tech. in Intelligent Control, Environ., Comput. & Communi. Engineering*, Bangalore, India, 2022, pp. 1–6.

[43] B. Xu, R. Wang, B. Peng, F. A. Alqurashi, and M. Salama, "Automatic parameter selection ZVD shaping algorithm for crane vibration

suppression based on particle swarm optimisation," *Appl. Math. Nonlinear Sci.*, vol. 7, no. 1, pp. 73–82, Jan. 2022.

[44] L. Ramli, Z. Mohamed, and H. I. Jaafar, "A neural network-based input shaping for swing suppression of an overhead crane under payload hoisting and mass variations," *Mech. Syst. Signal Process.*, vol. 107, pp. 484–501, Jul. 2018.

[45] W. Tang, R. Ma, W. Wang, and H. Gao, "Optimization-based input-shaping swing control of overhead cranes," *Appl. Sci.*, vol. 13, no. 17, p. 9637, Aug. 2023.

[46] H. I. Jaafar, Z. Mohamed, M. A. Shamsudin, N. A. M. Subha, L. Ramli, and A. M. Abdullahi, "Model reference command shaping for vibration control of multimode flexible systems with application to a double-pendulum overhead crane," *Mech. Syst. Signal Process.*, vol. 115, pp. 677–695, Jan. 2019.

[47] H. I. Jaafar, Z. Mohamed, M. A. Ahmad, N. A. Wahab, L. Ramli, and M. H. Shaheed, "Control of an underactuated double-pendulum overhead crane using improved model reference command shaping: Design, simulation and experiment," *Mech. Syst. Signal Process.*, vol. 151, p. 107358, Apr. 2021.

[48] M.-N. Pham, B. Hazel, P. Hamelin, and Z. Liu, "Vibration control of flexible joint robots using a discrete-time two-stage controller based on time-varying input shaping and delay compensation," *J. Dyn. Syst., Meas. Control*, vol. 143, no. 10, p. 101001, Oct. 2021.

[49] A. Stein and T. Singh, "Input shaped control of a gantry crane with inertial payload," in *Proc. American Control Conf.*, Atlanta, USA, 2022, pp. 4127–4132.

[50] Y. Du, X. Song, and B. Han, "Improvement and experimental research on high-speed magnetic blower and pipeline system," *J. Vib. Meas. Diagn.*, vol. 39, no. 3, pp. 512–517, Jun. 2019.

[51] S. Zou, B. Pan, Y. Fu, and S. Guo, "Position control and vibration suppression for flexible-joint surgical robot," in *Proc. 3rd Int. Conf. Control, Robotics and Cybern.*, Penang, Malaysia, 2018, pp. 42–47.

[52] J. Xu, H. Fang, T. Zhou, Y.-H. Chen, H. Guo, and F. Zeng, "Optimal robust position control with input shaping for flexible solar array drive system: A fuzzy-set theoretic approach," *IEEE Trans. Fuzzy Syst.*, vol. 27, no. 9, pp. 1807–1817, Sep. 2019.

[53] J.-H. Shin, D.-H. Lee, and M. K. Kwak, "Vibration suppression of cart-pendulum system by combining the input-shaping control and the position-input position-output feedback control," *J. Mech. Sci. Technol.*, vol. 33, no. 12, pp. 5761–5768, Dec. 2019.

[54] D. Newman and J. Vaughan, "Concurrent design of linear control with input shaping for a two-link flexible manipulator arm," *IFAC-PapersOnLine*, vol. 51, no. 14, pp. 66–71, Jan. 2018.

[55] B. B. Kang, "Specified-duration shapers for suppressing residual vibrations," *PLoS One*, vol. 17, no. 11, p. e0276669, Nov. 2022.

[56] C.-G. Kang, R. Hassan, and K.-Y. Kim, "Analysis of a generalized ZVD shaper using impulse vectors," *Int. J. Control Autom. Syst.*, vol. 18, no. 8, pp. 2088–2094, Feb. 2020.

[57] B. Li, Y.-L. Wei, P.-F. Ou, and Q.-Z. Zhang, "Robustness analysis on vibration reduction of negative impulses hybrid multiple-modal input shapers," *Mach. Des. Manuf.*, no. 1, pp. 132–135, Jan. 2020.

[58] Y. Wei, B. Li, Q. Zhang, and P. Ou, "Quick suppression of vibration of robot via hybrid input shaping control strategy," *J. Northwestern Polytechnical Univ.*, vol. 37, no. 3, pp. 636–641, Jun. 2019.

[59] X. Cao, C. Meng, Y. Zhou, and M. Zhu, "An improved negative zero vibration anti-swing control strategy for grab ship unloader based on elastic wire rope model," *Mech. Ind.*, vol. 22, no. 45, pp. 1–10, Nov. 2021.

[60] L. Li, X. Hu, and Y. Zou, "Residual vibration suppression by an integrated method of parameter identification and input shaping," *J. Vib. Meas. Diagn.*, vol. 39, no. 3, pp. 565–570, Jun. 2019.

[61] C. Liu and Y. Chen, "Combined S-curve feedrate profiling and input shaping for glass substrate transfer robot vibration suppression," *Ind. Rob.*, vol. 45, no. 4, pp. 549–560, Aug. 2019.

[62] A. Gavula, P. Hubinský, and A. Babinec, "Damping of oscillations of a rotary pendulum system," *Appl. Sci.*, vol. 13, no. 21, p. 11946, Nov. 2023.

[63] P. Kuresangsai and M. O. T. Cole, "Control of a nonlinear flexure-jointed X-Y positioning stage using LTV-FIR command prefiltering for finite-time error cancellation," *Mech. Syst. Signal Process.*, vol. 151, p. 107349, Apr. 2021.

[64] S. M. Fasih, Z. Mohamed, A. R. Husain, L. Ramli, A. M. Abdullahi, and W. Anjum, "Payload swing control of a tower crane using a neural network-based input shaper," *Meas. Control*, vol. 53, no. 7–8, pp. 1171–1182, Aug.–Sep. 2020.

[65] L. Rincon, Y. Kubota, G. Venture, and Y. Tagawa, "Inverse dynamic control via "simulation of feedback control" by artificial neural networks for a crane system," *Control Eng. Pract.*, vol. 94, p. 104203, Jan. 2020.

[66] J. J. Wilbanks and M. J. Leamy, "Robust two-scale command shaping for residual vibration mitigation in nonlinear systems," *J. Sound Vib.*, vol. 462, p. 114927, Dec. 2019.

[67] M. M. İlman, Ş. Yavuz, and P. Y. Taser, "Generalized input preshaping vibration control approach for multi-link flexible manipulators using machine intelligence," *Mechatronics*, vol. 82, p. 102735, Apr. 2022.

[68] S. F. ur Rehman, Z. Mohamed, A. R. Husain, L. Ramli, M. A. Abbasi, W. Anjum, and M. H. Shaheed, "Adaptive input shaper for payload swing control of a 5-DOF tower crane with parameter uncertainties and obstacle avoidance," *Autom. Constr.*, vol. 154, p. 104963, Oct. 2023.

[69] D. Bruijnen and N. van Dijk, "Combined input shaping and feedforward control for flexible motion systems," in *Proc. American Control Conf.*, Montreal, Canada, 2012, pp. 2473–2478.

[70] L. Yang and H. Zhang, "Data-driven feedforward parameter tuning optimization method under actuator constraints," *IEEE/ASME Trans. Mechatron.*, vol. 27, no. 5, pp. 3429–3439, Oct. 2022.

[71] F. Boeren, D. Bruijnen, N. van Dijk, and T. Oomen, "Joint input shaping and feedforward for point-to-point motion: Automated tuning for an industrial nanopositioning system," *Mechatronics*, vol. 24, no. 6, pp. 572–581, Sep. 2014.

[72] M. Heertjes and D. Bruijnen, "MIMO FIR feedforward design for zero error tracking control," in *Proc. American Control Conf.*, Portland, USA, 2014, pp. 2166–2171.

[73] M. Giacomelli, M. Faroni, D. Gorni, A. Marini, L. Simoni, and A. Visioli, "Model Predictive Control for operator-in-the-loop overhead cranes," in *Proc. IEEE 23rd Int. Conf. Emerging Technologies and Factory Automation*, Turin, Italy, 2018, pp. 589–596.

[74] W. Tang, R. Ma, W. Wang, T. Xu, H. Gao, and X. Wang, "Composite control of overhead cranes based on input shaper and PID," in *Proc. 42nd Chinese Control Conf.*, Tianjin, China, 2023, pp. 2568–2572.

[75] A. Dautt-Silva and R. A. de Callafon, "Reference signal shaping for closed-loop systems with causality constraints," in *Proc. 60th IEEE Conf. Decision and Control*, Austin, USA, 2021, pp. 1838–1843.

[76] I. A. Martin and R. A. Irani, "Evaluation of both linear and non-linear control strategies for a shipboard marine gantry crane," in *Proc. OCEANS MTS/IEEE SEATTLE*, Seattle, USA, 2019, pp. 1–10.

[77] P. B. de Moura Oliveira and D. Vrančić, "Practical validation of a dual mode feedforward-feedback control scheme in an Arduino kit," in *Proc. 14th APCA Int. Conf. Automatic Control and Soft Computing*, Bragança, Portugal, 2020, pp. 538–547.

[78] J. Oliveira, P. M. Oliveira, T. M. Pinho, and J. B. Cunha, "PID posicast control for uncertain oscillatory systems: A practical experiment," *IFAC-PapersOnLine*, vol. 51, no. 4, pp. 416–421, Jan. 2018.

[79] M. D. Duong, Q. T. Dao, and T. H. Do, "Settling time optimization of a critically damped system with input shaping for vibration suppression control," *Eng. Technol. Appl. Sci. Res.*, vol. 12, no. 5, pp. 9388–9394, Oct. 2022.

[80] Q. Cui, Y. Xue, D. Li, and L. Sun, "A robust control methodology based on active disturbance rejection control and input shaping," in *Proc. 18th Int. Conf. Control, Auto. and Systems*, PyeongChang, South

Korea , 2018, pp. 968–973.

[81] M. Abdullah and J. A. Rossiter, "Input shaping predictive functional control for different types of challenging dynamics processes," *Processes*, vol. 6, no. 8, p. 118, Aug. 2018.

[82] G. A. Kocak, H. H. Bilgic, and C. Conker, "A fuzzy logic-based intelligent decision support system for the selection of an appropriate input-shaping technique for controlling flexible link systems," *Int. J. Modell. Simul.*, vol. 42, no. 5, pp. 868–881, Nov. 2021.

[83] M. Yuan, L. Wang, W. Chen, B. Qiu, and Y. Xu, "Vibration suppression for forging robots based on input shaping and sliding mold," *Comput. Integr. Manuf. Syst.*, vol. 28, no. 1, pp. 102–111, Jan. 2022.

[84] X. Shan, Y. Li, H. Liu, and T. Huang, "Residual vibration reduction of high-speed pick-and-place parallel robot using input shaping," *Chin. J. Mech. Eng.*, vol. 35, no. 1, p. 16, Feb. 2022.

[85] K. Alghanim, A. Mohammed, and M. T. Andani, "An input shaping control scheme with application on overhead cranes," *Int. J. Nonlinear Sci. Numer. Simul.*, vol. 20, no. 5, pp. 561–573, Apr. 2019.

[86] C.-G. Kang, "Impulse vectors for input-shaping control: A mathematical tool to design and analyze input shapers," *IEEE Control Syst. Mag.*, vol. 39, no. 4, pp. 40–55, Aug. 2019.

[87] L. Li, X.-Q. Hu, Y.-B. Zou, and X.-G. Liu, "Reducing vibration by error compensation input shaping technique," *J. Vib. Eng.*, vol. 32, no. 6, pp. 996–1002, Dec. 2019.

[88] Z. Li, H. Zhao, and H. Ding, "Optimization of contact control in grinding and polishing process of industrial blades," *Modular Mach. Tool Autom. Manuf. Tech.*, vol. 2, no. 2, pp. 99–106, Feb. 2021.

[89] P. Du, W. Niu, and C. Chen, "Crane anti swing method based on input shaping with pulse input," *Comput. Meas. Control*, vol. 26, no. 10, pp. 235–239, Mar. 2018.

[90] Y. Zhao and M. Tomizuka, "Modified zero time delay input shaping for industrial robot with flexibility," in *Proc. ASME Dynamic Systems and Control Conf.*, Tysons, USA, 2017, pp. 1–6.

[91] M. Zhang, H. Zou, H. Wang, and G. Tang, "Vibration suppression during operation of mechanical arm with two degrees of freedom based on input shaping method," *Aerosp. Shanghai (Chin. Engl.)*, vol. 37, no. 5, pp. 37–42, May 2020.

[92] T. Zhang, K. Lin, Y. Zou, and X. Liu, "An input shaper with control of error optimization for end-effector's residual vibration suppression of industrial robots," *J. Xi'an Jiaotong Univ.*, vol. 52, no. 4, pp. 90–97, Apr. 2018.

[93] L. Li, Z.-C. Gu, and T. Zhang, "Adaptive vibration suppression control for trajectory motion in Cartesian space of industrial robot," *J. Vib. Eng.*, vol. 34, no. 3, pp. 499–506, Jun. 2021.

[94] W. Wang, C. Hu, K. Zhou, and Z. Wang, "Time parameter mapping and contour error precompensation for multiaxis input shaping," *IEEE Trans. Ind. Inf.*, vol. 19, no. 3, pp. 2640–2651, Mar. 2023.

[95] F. Bi, X. Luo, B. Shen, H. Dong, and Z. Wang, "Proximal alternating-direction-method-of-multipliers-incorporated nonnegative latent factor analysis," *IEEE/CAA J. Autom. Sinica*, vol. 10, no. 6, pp. 1388–1406, Jun. 2023.

[96] M. J. Maghsoudi, L. Ramli, S. Sudin, Z. Mohamed, A. R. Husain, and H. Wahid, "Improved unity magnitude input shaping scheme for sway control of an underactuated 3D overhead crane with hoisting," *Mech. Syst. Signal Process.*, vol. 123, pp. 466–482, May 2019.

[97] M. Newman, K. Lu, and M. Khoshdarregi, "Suppression of robot vibrations using input shaping and learning-based structural models," *J. Intell. Mater. Syst. Struct.*, vol. 32, no. 9, pp. 1001–1012, May 2021.

[98] D. K. Thomsen, R. Søe-Knudsen, D. Brandt, O. Balling, and X. Zhang, "Smooth online time-varying input shaping with fractional delay FIR filtering," *Control Eng. Pract.*, vol. 88, pp. 21–37, Jul. 2019.

[99] J. Kim and E. A. Croft, "Preshaping input trajectories of industrial robots for vibration suppression," *Rob. Comput.-Integr. Manuf.*, vol. 54, pp. 35–44, Dec. 2018.

[100] T. Wang, T. Zhang, A. Song, and Y. Zhang, "An input shaping based active vibration control and adaptive RBF impedance control for suppressing the myospasm in upper-limb rehabilitation," *Appl. Soft Comput.*, vol. 95, p. 106380, Oct. 2020.

[101] M. Vu, D. Newman, and J. Vaughan, "Designing input shapers using reinforcement learning," in *Proc. Annu. American Control Conf.*, Milwaukee, USA, 2018, pp. 228–-233.

[102] S. M. Fasih ur Rehman, Z. Mohamed, A. R. Husain, H. I. Jaafar, M. H. Shaheed, and M. A. Abbasi, "Input shaping with an adaptive scheme for swing control of an underactuated tower crane under payload hoisting and mass variations," *Mech. Syst. Signal Process.*, vol. 175, p. 109106, Aug. 2022.

[103] T. Zhang, Z. Kang, Y. Zou, and C. Liao, "Deep neural network input shaper for residual vibration suppression," *J. South China Univ. Technol. (Nat. Sci. Ed.)*, vol. 49, no. 8, pp. 103–112, Aug. 2021.

[104] L. Ramli, Z. Mohamed, M. Ö. Efe, I. M. Lazim, and H. I. Jaafar, "Efficient swing control of an overhead crane with simultaneous payload hoisting and external disturbances," *Mech. Syst. Signal Process.*, vol. 135, p. 106326, Jan. 2020.

[105] C. Bergeling, R. Pates, and A. Rantzer, "H-infinity optimal control for systems with a bottleneck frequency," *IEEE Trans. Autom. Control*, vol. 66, no. 6, pp. 2732–2738, Jun. 2021.

[106] S. Nithi-Uthai and W. Chatlatanagulchai, "Improved backstepping controller for rigid-flexible system using input shaping reference model matching and neural network," in *Proc. 58th Ann. Conf. Society of Instrument and Control Engineers of Japan*, Hiroshima, Japan, 2019, pp. 1024–1029.

[107] J. Xu, J. Cao, and Y. Zhang, "Vibration suppression of picking device with improved input shaping algorithm," *J. Northeast For. Univ.*, vol. 48, no. 12, pp. 79–84, Dec. 2020.

[108] T. Zhang, H. Chu, Y. Zou, and T. Liu, "A deep reinforcement learning-based optimization method for vibration suppression of articulated robots," *Eng. Optim.*, vol. 55, no. 7, pp. 1189–1206, May 2023.

[109] L. Chen and X. Luo, "Tensor distribution regression based on the 3D conventional neural networks," *IEEE/CAA J. Autom. Sinica*, vol. 10, no. 7, pp. 1628–1630, Jul. 2023.

[110] K. Yin, H. Wang, L. Zhong, T. Zhang, J. Ye, and Y. La, "Research on feed forward force/position hybrid control strategy of robot flexible joint," *Mach. Tool Hydraul.*, vol. 50, no. 11, pp. 25–34, Jun. 2022.

[111] Y. Zou, T. Liu, T. Zhang, and H. Chu, "A learning trajectory planning for vibration suppression of industrial robot," *Ind. Rob.*, vol. 50, no. 5, pp. 861–869, May 2023.

[112] T. Zhang, K. Lin, and A. Zhang, "Research on flexible dynamics of a 6-DOF industrial robot and residual vibration control with a pre-adaptive input shaper," *J. Mech. Sci. Technol.*, vol. 33, no. 4, pp. 1875–1889, Apr. 2019.

[113] R. Jallouli-Khlif, B. Maalej, P. Melchior, and N. Derbel, "Control of prosthetic hand based on input shaping combined to fractional PI controller," in *Proc. 9th Int. Conf. Systems and Control*, Caen, France, 2021, pp. 449–454.

[114] L. Li, Q. Zhang, T. Zhang, and Y. Zou, "Vibration suppression of ball-screw drive system based on flexible dynamics model," *Eng. Appl. Artif. Intell.*, vol. 117, p. 105506, Jan. 2023.

[115] A. Mohammed, H. Altuwais, and K. Alghanim, "An optimized shaped command of overhead crane nonlinear system for rest-to-rest maneuver," *J. Eng. Res.*, vol. 11, no. 4, pp. 548–554, Dec. 2023.

[116] P. Jia, Y. Zhou, and X. Li, "Vibration control of a flexible joint manipulator based on off-line learning input shaping," *J. Vib. Shock*, vol. 37, no. 13, pp. 177–181, May 2018.

[117] S. Patel and W. Weaver, "Input shaping control of paralleled DC-DC converters," in *Proc. IEEE Energy Conversion Congr. Expo.*, Detroit, USA, 2020, pp. 2619–2624.

[118] Z. Pásztori, F. Ruggiero, V. Lippiello, and M. D. Castro, "Bayesian optimization approach to input shaper design for flexible beam vibration suppression," *IFAC-PapersOnLine*, vol. 53, no. 2, pp. 9150–9156, Jan. 2020.

[119] X. Zhang, Q. Zong, B. Tian, and W. Liu, "Continuous robust fault-

tolerant control and vibration suppression for flexible spacecraft without angular velocity," *Int. J. Robust Nonlinear Control*, vol. 29, no. 12, pp. 3915–3935, Aug. 2019.

[120] L. Hu, S. Yang, X. Luo, H. Yuan, K. Sedraoui, and M. C. Zhou, "A distributed framework for large-scale protein-protein interaction data analysis and prediction using MapReduce," *IEEE/CAA J. Autom. Sinica*, vol. 9, no. 1, pp. 160–172, Jan. 2022.

[121] X. Miao, L. Yang, and H. Ouyang, "Artificial-neural-network-based optimal Smoother design for oscillation suppression control of underactuated overhead cranes with distributed mass beams," *Mech. Syst. Signal Process.*, vol. 200, p. 110497, Oct. 2023.

[122] A. Al-Fadhli and E. Khorshid, "A smooth optimized input shaping method for two-dimensional crane systems using Bezier curves," *Trans. Inst. Meas. Control*, vol. 43, no. 11, pp. 2512–2524, Apr. 2021.

[123] T. Chen, Y. Wang, H. Wen, and J. Kang, "Autonomous assembly of multiple flexible spacecraft using RRT* algorithm and input shaping technique," *Nonlinear Dyn.*, vol. 111, no. 12, pp. 11223–11241, Apr. 2023.

[124] W. Chen, K.-S. Chen, and M.-C. Tsai, "Finite element input shaping design for vibration suppression of mechatronics systems," in *Proc. IEEE Int. Conf. Mechatronics*, Ilmenau, Germany, 2019, pp. 37–42.

[125] D. K. Thomsen, R. Søe-Knudsen, D. Brandt, and X, Zhang, "Experimental implementation of time-varying input shaping on UR robots," in *Proc. 16th Int. Conf. Informatics in Control, Automation and Robotics*, Prague, Czech Republic, 2019, pp. 488–498.

[126] P. P. Sahoo and W. Singhose, "Effects of input shaping on impact loads during collisions involving flexible robots," in *Proc. IEEE 14th Int. Conf. Control and Autom.*, Anchorage, USA, 2018, pp. 1004–1009.

[127] D. Wu and X. Luo, "Robust latent factor analysis for precise representation of high-dimensional and sparse data," *IEEE/CAA J. Autom. Sinica*, vol. 8, no. 4, pp. 796–805, Apr. 2021.

[128] S. Arabasi and Z. Masoud, "Frequency-modulation input-shaping strategy for double-pendulum overhead cranes undergoing simultaneous hoist and travel maneuvers," *IEEE Access*, vol. 10, pp. 44954–44963, Apr. 2022.

[129] Y. Shi, W. Zhao, S. Li, B. Li, and X. Sun, "Novel discrete-time recurrent neural network for robot manipulator: A direct discretization technical route," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 34, no. 6, pp. 2781–2790, Jun. 2023.

[130] G.-Y. Jung, S.-B. Choi, and G.-W. Kim, "Series Ni-Ti shape memory alloy wires with different martensitic-austenitic phase transformation temperatures as an actuator for input shaping control," *Smart Mater. Struct.*, vol. 28, no. 7, p. 77001, May 2019.

[131] A. Al-Fadhli and E. Khorshid, "Payload oscillation control of tower crane using smooth command input," *J. Vib. Control*, vol. 29, no. 3–4, pp. 902–915, Feb. 2023.

[132] W. Kim, Y. Shin, T. Kim, and C.-G. Kang, "Modeling analysis for system parameters of a vertical input shaping control apparatus," in *Proc. 12th Asian Control Conf.*, Kitakyushu, Japan, 2019, pp. 1205–1209.

[133] J. Cao, M. Yang, and D. Xu, "Supression of vibration of AC servo system based on input shaping technique," in *Proc. 21st Int. Conf. Electrical Machines and Systems*, Jeju, South Korea, 2018, pp. 2593–2597.

[134] X. Li, Z. Xu, S. Li, Z. Su, and X. Zhou, "Simultaneous obstacle avoidance and target tracking of multiple wheeled mobile robots with certified safety," *IEEE Trans. Cybern.*, vol. 52, no. 11, pp. 11859–11873, Nov. 2022.

[135] K. A. Alhazza, Z. N. Masoud, and J. A. Alqabandi, "A close-form command shaping control for point-to-point maneuver with nonzero initial and final conditions," *Mech. Syst. Signal Process.*, vol. 170, p. 108804, May 2022.

[136] L. Jin, X. Zheng, and X. Luo, "Neural dynamics for distributed collaborative control of manipulators with time delays," *IEEE/CAA J. Autom. Sinica*, vol. 9, no. 5, pp. 854–863, May 2022.

[137] G. Jin and M. Deng, "Operator-based robust nonlinear free vibration control of a flexible plate with unknown input nonlinearity," *IEEE/CAA J. Autom. Sinica*, vol. 7, no. 2, pp. 442–450, Mar. 2020.

[138] T. Rome, W. Singhose, K. Dobson, K. Sorensen, F. Schlagenhauf, and J.-W. Kang, "Impact of input shaper discretization on linear resonant actuators for haptic feedback," in *Proc. IEEE 31st Int. Symp. Industrial Electronics*, Anchorage, USA, 2022, pp. 194–199.

[139] Y. Yuan, J. Li, and X. Luo, "A fuzzy PID-incorporated stochastic gradient descent algorithm for fast and accurate latent factor analysis," *IEEE Trans. Fuzzy Systems*, vol. 32, no. 7, pp. 4049–4061, Jul. , 2024.

[140] G. Chen, L. Zhu, W. Zheng, and C. Wang, "Vibration suppression in a two-mass drive system using three input shaping — Comparative study," in *Proc. Int. Conf. Computing, Electronics & Communications Engineering*, Swansea, UK, 2023, pp. 68–73.

[141] C. Li, X. Huo, and Q. Liu, "A new robust command shaping method and its application in quadrotor slung system with varying parameters," *IFAC-PapersOnLine*, vol. 53, no. 2, pp. 5737–5742, Jan. 2020.

[142] X. Cao and S. Li, "A novel dynamic neural system for nonconvex portfolio optimization with cardinality restrictions," *IEEE Trans. Syst., Man, Cybern.: Syst.*, vol. 53, no. 11, pp. 6943–6952, Nov. 2023.

[143] J.-H. Montonen, N. Nevaranta, M. Niemelä, and T. Lindh, "Comparison of extrainsensitive input shaping and swing-angle-estimation-based slew control approaches for a tower crane," *Appl. Sci.*, vol. 12, no. 12, p. 5945, Jun. 2022.

[144] G. Peláez, J. Vaugan, P. Izquierdo, H. Rubio, and J. C. García-Prada, "Dynamics and embedded internet of things input shaping control for overhead cranes transporting multibody payloads," *Sensors*, vol. 18, no. 6, p. 1817, Jun. 2018.

[145] A. Bhayadia, A. Olivett, T. Singh, and M. A. Karami, "Input shaping for travelling wave generation," *Smart Mater. Struct.*, vol. 31, no. 5, p. 055006, Mar. 2022.

[146] Y. Zhang, S. Li, and G. Geng, "Initialization-based *k*-winners-take-all neural network model using modified gradient descent," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 34, no. 8, pp. 4130–4138, Aug. 2023.

[147] B. Lu, Z. Wu, Y.-C. Fang, and N. Sun, "Input shaping control for underactuated dual overhead crane system with holonomic constraints," *Control Theory Appl.*, vol. 35, no. 12, pp. 1805–1811, Dec. 2018.

[148] X. Luo, H. Wu, Z. Wang, J. Wang, and D. Meng, "A novel approach to large-scale dynamically weighted directed network representation," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 44, no. 12, pp. 9756–9773, Dec. 2022.

[149] Y. Shi, J. Wang, S. Li, B. Li, and X. Sun, "Tracking control of cable-driven planar robot based on discrete-time recurrent neural network with immediate discretization method," *IEEE Trans. Ind. Inf.*, vol. 19, no. 6, pp. 7414–7423, Jun. 2023.

[150] C. Zhu, B. Chen, M. Zhang, and G.-A. Tang, "Suppression of spacecraft vibration excitation during attitude adjustment with input shaping using drive assembly," *Manned Spaceflight*, vol. 24, no. 4, pp. 488–493, Aug. 2018.

[151] X. Zhang, Q. Zong, L. Dou, B. Tian, and W. Liu, "Finite-time attitude maneuvering and vibration suppression of flexible spacecraft," *J. Franklin Inst.*, vol. 357, no. 16, pp. 11604–11628, Nov. 2020.

[152] S. Jia and J. Shan, "Vibration control of gyroelastic spacecraft using input shaping and angular momentum devices," *Acta Astronaut.*, vol. 159, pp. 397–409, Jun. 2019.

[153] H. Wu, X. Luo, M. C. Zhou, M. J. Rawa, K. Sedraoui, and A. Albeshri, "A PID-incorporated latent factorization of tensors approach to dynamically weighted directed network analysis," *IEEE/CAA J. Autom. Sinica*, vol. 9, no. 3, pp. 533–546, Mar. 2022.

[154] S. Baklouti, E. Courteille, P. Lemoine, and S. Caro, "Input shaping for feed-forward control of cable-driven parallel robots," *J. Dyn. Syst., Meas., Control*, vol. 143, no. 2, p. 021007, Feb. 2021.

[155] W. Zhu, Q. Zong, and B. Tian, "Adaptive tracking and command shaped vibration control of flexible spacecraft," *IET Control Theory Appl.*, vol. 13, no. 8, pp. 1121–1128, May 2019.

[156] Y. Yang, L. Liao, H. Yang, and S. Li, "An optimal control strategy for multi-UAVs target tracking and cooperative competition," *IEEE/CAA J. Autom. Sinica*, vol. 8, no. 12, pp. 1931–1947, Dec. 2021.

[157] K. Alghanim, A. Alfadhli, A. Alshehemah, and A. Mohammed, "Crane systems performance optimization through harmonic input shaper," *Int. J. Dyn. Control*, vol. 12, no. 6, pp. 1788–1800, Jun. 2024.

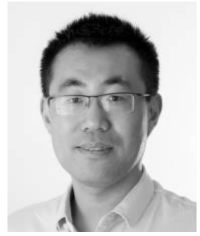
[158] A. Stein and T. Singh, "Minimum time control of a gantry crane system with rate constraints," *Mech. Syst. Signal Process.*, vol. 190, p. 110120, May 2023.

[159] Z. Liu, G. Yuan, and X. Luo, "Symmetry and nonnegativity-constrained matrix factorization for community detection," *IEEE/CAA J. Autom. Sinica*, vol. 9, no. 9, pp. 1691–1693, Sep. 2022.

[160] T. Zhang and G. Liu, "Predictive tracking control of network-based agents with communication delays," *IEEE/CAA J. Autom. Sinica*, vol. 5, no. 6, pp. 1150–1156, Nov. 2018.

[161] H. D. Tho, K. Terashima, and T. Miyoshi, "Vibration control of an overhead crane with hoisting motion using input shaping technique," in *Proc. American Control Conf.*, Atlanta, USA, 2022, pp. 1910–1914.

Weiyi Yang received the B.S. degree in software engineering from the Yunnan University in 2021. She is a Ph.D. candidate in computer software and theory at the Chongqing Institute of Green and Intelligent Technology, Chinese Academy of Sciences. She is currently also with the University of Chinese Academy of Sciences. Her research interests include articulated manipulator calibration, input shaping, big data analysis, and algorithm design for large-scale data applications.



Shuai Li (Senior Member, IEEE) received the B.E. degree in precision mechanical engineering from the Hefei University of Technology in 2005, the M.E. degree in automatic control engineering from the University of Science and Technology of China in 2008, and the Ph.D. degree in electrical and computer engineering from the Stevens Institute of Technology, USA in 2014. He is currently a Full Professor with the Faculty of Information Technology and Electrical Engineering, University of Oulu, Finland, and also serve as an Adjunct Professor with National Technology Research Center of Finland (VTT). His current research interests include dynamic neural networks, robotics, machine learning, and autonomous systems.

Xin Luo (Senior Member, IEEE) received the B.S. degree in computer science from the University of Electronic Science and Technology of China in 2005, and the Ph.D. degree in computer science from the Beihang University in 2011. He is currently a Professor of data science and computational intelligence with the College of Computer and Information Science, Southwest University. His research interests include big data analysis and intelligent control.

Dr. Luo has authored or coauthored over 200 papers (including over 130 IEEE Transactions papers) in the areas of his interests. He was the recipient of the Outstanding Associate Editor Award from *IEEE/CAA Journal of Automatica Sinica* in 2020, and from *IEEE Transactions on Neural Networks and Learning Systems* in 2022. He is currently serving as an Associate Editor for *IEEE Transactions on Neural Networks and Learning Systems*, and *IEEE/CAA Journal of Automatica Sinica*. .