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MODIFIED MODEL-FREE ADAPTIVE PREDICTIVE CONTROL APPLIED TO VIBRATION REDUCTION OF MECHANICAL FLEXIBLE SYSTEMS

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ABSTRACT

Model predictive control (MPC) has become more attractive in control engineering for the last decades because of its efficiency and robustness. In this paper, an effective control strategy is proposed for vibration reduction of mechanical flexible systems in which establishment of a global dynamic model of the controlled system is not necessary. A modified model-free adaptive predictive controller is designed by combination of MPC and model-free control theory. The novel idea of this contribution is that by using the compact-form dynamic linearization technique, the upcoming system outputs within a specified prediction horizon can be predicted in sequence. The data-based prediction model of the system only requires input/output information, and therefore the future control input increments as well as the unknown system parameters called pseudo-jacobian matrix can be estimated. To improve parameter estimation accuracy, another online estimation method namely recursive least-squares algorithm is applied instead of using the conventional projection algorithm. The control performance is verified nummerically for vibration control of a flexible ship-mounted crane represented as a multi-input multi-output (MIMO) system. Simulation results indicate that significant reduction of the crane oscillations and better control performance are observed when using the proposed controller in comparison with other traditional methods.

INTRODUCTION

Since the last few years, an alternative solution to deal with control design of unknown MIMO nonlinear systems has been introduced namely model-free control (MFC) beside a variety of existing model-based control (MBC) methods. The basic assumption for this type of control is that the required controller can be designed by using only online or offline input/output (I/O) data which are measured or calculated directly from the controlled system [1]. An accurate mathematical model of the considered system is not necessary to be fully known. Therefore, no information about model structures, unmodeled dynamics or uncertainties which are important in MBC needs to be investigated. As a typical MFC, model-free adaptive control (MFAC) was firstly proposed by Z. S. Hou et al. [2] and has been applied to a class of single-input single-output (SISO) as well as MIMO nonlinear systems [3–7]. Based on different dynamic linearization techniques such as compact-form, partial-form, and full-form dynamic linearization [2], an equivalent linearized data model of the original system is locally established which contains unknown time-varying parameters. These parameters can be estimated and updated recursively at every time-instant of the system operation based on the previous system inputs and outputs. As result, the required control input signals can be determined by minimization of an objective function using the corrected system parameters and the current control errors. As discussed in [2], MFAC possesses several attractive properties compared to MBC. First, only the I/O data obtaining from the closed-loop system are used to design controllers. Second, MFAC does not require any external testing signals as well as training processes. Furthermore, MFAC may have simple structures leading to low computational load. Finally, the convergence and stability of MFAC algorithms can be guaranteed under some reasonable assumptions [2].

Model predictive control or MPC has been proved as one of the most effective control methods since 1970s, which is particularly useful for constrained control problems. The theory of MPC is basically related to using an explicit system model to predict the future process ouputs within a range of future time-instants (prediction horizon) [8]. Afterwards, based on the estimated control errors, a control input sequence can be calculated and the first control signal is applied to fulfill the initial control requirements. Up to now, a variety of MPC algorithms and its modifications have been proposed to cope with the problem of process noises or measurable disturbances. As presented in [9], the author reviewed the three decade development of MPC in both research and industrial/commercial activities. Particularly, a survey of industrial MPC technology is addressed in [10] which provides an overview of commercially available MPC techniques for linear and nonlinear control systems.

By combination of MPC and MFC theories, different adaptive control algorithms are developed for nonlinear dynamical systems. K. K. Tan et al. [11] proposed a new robust adaptive predictive proportional-integral (PI) controller which uses standard recursive least-squares algorithms for system parameter estimation. In [12], a novel data-driven model-free adaptive predictive control (MFAPC) strategy based on lazy-learning technique is designed only for SISO nonlinear discrete-time systems. In addition, based on the compact-form dynamic linearization (CFDL) concept [2], an extended MFAPC scheme is designed for multivariate molten iron quality data [13]. A modified projection algorithm is proposed to estimate and update the unknown parameter matrix called pseudo-partial derivative (PPD) [13]. Recently, Y. Guo et al. [14] introduce a novel MFAPC program for MIMO nonlinear systems with stability analysis based on a series of reasonable assumptions. To design the controller, the modified projection algorithm as discussed in [2] is needed.

In this contribution, a modified MFAPC scheme is proposed concerning on vibration reduction of mechanical flexible systems. The designed controller is applied to an elastic crane representing a typical MIMO system. Motion-induced vibrations are serious problems which should be suppressed or reduced passively or actively. Study of vibration control applying to the field of elastic mechanical systems is highly motivated. In general, a comprehensive review of crane types and control issues including a brief review on modeling of single-pendulum and double-pendulum crane structures is discussed by L. Ramli et al. [15]. To control both the sway and the vibration by the inherent capability of tower cranes, the authors in [16] propose a decentralized control program which indicates better performance compared with a centralized one. In addition, an adaptive control approach for a flexible crane system with a boundary output constraint is described in [17]. A flexible cable with a payload attached at the bottom is considered to be the model of the crane. Obviously, the system modeling is essential for control design. As an illustrative example, a robust nonlinear controller using adaptive repetitive learning control method is proposed by Y. Qian et al. [18] for an offshore boom crane in which external disturbances effect strongly to the controlled system.

However, most of the aboved approaches require system models which could be very difficult to obtain, especially for MIMO nonlinear systems. Different from MBC, this contribution discusses a modified model-free adaptive predictive control method for a class of mechanical flexible structures. The modified idea is implemented by applying the modified recursive least-squares algorithm (RLSA) [2] to improve parameter estimation accuracy. Then, the predicted system outputs and the future control inputs are calculated by using the updated system parameters. The proposed controller is used to reduce oscillations of the elastic boom and the payload of a crane. The remaining parts of the paper are organized as follows. In Section II, a CFDL-based prediction model within context of MIMO cases is established for system output prediction. Detail discussion about using the modified RLSA for the CFDL model is illustrated. In Section III, discussion about the calculation of the control input signals and some steps to design the control program is described. Vibration control example with simulation results and discussion are shown in Section IV. Finally, a conclusion will be given in the last section.

COMPACT-FORM DYNAMIC LINEARIZATION-BASED PREDICTION MODEL

In this section, a general compact-form of N-step-ahead prediction equation is established based on the CFDL concept [2]. This linearized dynamical form contains unknown time-varying parameters which could be estimated and predicted recursively. For online parameter estimation, instead of using conventional projection algorithm as introduced in [12, 14], this contribution discusses recursive least-squares algorithm [19] for estimation accuracy improvement. The updated parameters are utilized to predict the future control inputs, and therefore to fulfill the control requirements.

General compact-form predictive equation

According to [2], for a class of unknown MIMO nonlinear systems, a general I/O description can be illustrated in discrete-time as

$$\mathbf{y}(k+1) = f(\mathbf{y}(k), ..., \mathbf{y}(k-m_y), \mathbf{u}(k), ..., \mathbf{u}(k-m_u)), \quad (1)$$

where $\mathbf{y}(k) \in R^r, \mathbf{u}(k) \in R^m$ denote the system outputs and control inputs at current step k, respectively. The unknown system orders represented as m_y and m_u, while m and r indicate the number of input and output signals, correspondingly. The unknown nonlinear function $f(...)$ contains the previous I/O values up to step k.

To establish an equivalent linearized form of the original system (1), according to [2], two reasonable assumptions should be satisfied as follows

Assumption 1: The partial derivatives of $f(...)$ with respect to $\mathbf{u}(k)$ exist and are considered as smooth.

Assumption 2: The system (1) satisfies the general Lipschitz condition $\|\mathbf{y}(k+1) - \mathbf{y}(k)\| \leq b\|\mathbf{u}(k) - \mathbf{u}(k-1)\|$ at each time interval k with $\|\mathbf{u}(k) - \mathbf{u}(k-1)\| \neq 0$, and b is a positive constant. Assumption 2 defines an upper bound on the change rate of the output driven by the change rate of the control input.

Based on the above assumptions, the original unknown system (1) can be linearized locally at every discrete-time k of the system operation. The CFDL data-based model is described as

$$\Delta\mathbf{y}(k+1) = \Phi(k)\Delta\mathbf{u}(k), \quad (2)$$

where the unknown time-varying parameter matrix $\Phi(k)$ called pseudo-jacobian matrix (PJM) which should be estimated continuously. The structure of the PJM in MIMO case is written as

$$\Phi(k) = \begin{bmatrix} \phi_{11}(k) & \phi_{12}(k) & \phi_{13}(k) & \dots & \phi_{1m}(k) \\ \phi_{21}(k) & \phi_{22}(k) & \phi_{23}(k) & \dots & \phi_{2m}(k) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \phi_{r1}(k) & \phi_{r2}(k) & \phi_{r3}(k) & \dots & \phi_{rm}(k) \end{bmatrix}_{r\times m}, \quad (3)$$

assuming $\|\Phi(k)\| \leq b$ according to assumption 2.

In case of the number of system inputs and outputs are identical ($m = r = n$), another assumption needs to be given for system stability analysis [2] as

Assumption 3: The PJM matrix $\Phi(k)$ satisfies the diagonally dominant condition with the following conditions $|\phi_{ij}(k)| \leq c_1; c_2 \leq |\phi_{ii}(k)| \leq \alpha c_2$, whereas $i, j = 1, 2, \dots, n; i \neq j; \alpha \geq 1$, and the sign of all elements in $\Phi(k)$ are fixed. The two positive constants are c_1, c_2 and satisfy $c_2 > c_1(2\alpha+1)(n-1)$. As explained in [2], assumption 3 illustrates the coupling relationship between input and output in closed-loop data, that means the coupling among the system variables is described via the diagonal dominant matrix $\Phi(k)$.

The CFDL data model (2) also describes one-step-ahead prediction equation of the system output

$$\mathbf{y}(k+1) = \mathbf{y}(k) + \Phi(k)\Delta\mathbf{u}(k). \quad (4)$$

According to (4), N-step-ahead prediction equations of the system dynamics can be established as follows

$$\begin{cases} \mathbf{y}(k+1) = \mathbf{y}(k) + \Phi(k)\Delta\mathbf{u}(k) \\ \mathbf{y}(k+2) = \mathbf{y}(k+1) + \Phi(k+1)\Delta\mathbf{u}(k+1) \\ \mathbf{y}(k+2) = \mathbf{y}(k) + \Phi(k)\Delta\mathbf{u}(k) + \Phi(k+1)\Delta\mathbf{u}(k+1) \\ \vdots \\ \mathbf{y}(k+N_u) = \mathbf{y}(k+N_u-1) + \Phi(k+N_u-1)\Delta\mathbf{u}(k+N_u-1) \\ \vdots \\ \mathbf{y}(k+N) = \mathbf{y}(k+N-1) + \Phi(k+N-1)\Delta\mathbf{u}(k+N-1) \\ \mathbf{y}(k+N) = \mathbf{y}(k) + \Phi(k)\Delta\mathbf{u}(k) \\ +\dots + \Phi(k+N_u-1)\Delta\mathbf{u}(k+N_u-1) \\ +\dots + \Phi(k+N-1)\Delta\mathbf{u}(k+N-1) \end{cases}, \quad (5)$$

where N_u is the control input horizon with $1 \leq N_u \leq N$.

Let the following notations

$$\mathbf{Y}_N(k+1) = [\mathbf{y}(k+1), ..., \mathbf{y}(k+N_u), ..., \mathbf{y}(k+N)]^T, \quad (6)$$

$$\Delta\mathbf{U}_N(k) = [\Delta\mathbf{u}(k), ..., \Delta\mathbf{u}(k+N_u-1), ..., \Delta\mathbf{u}(k+N-1)]^T, \quad (7)$$

$$\mathbf{E}(k) = [\mathbf{I}_{r\times m}, \mathbf{I}_{r\times m}, ..., \mathbf{I}_{r\times m}]^T, \quad (8)$$

$$\mathbf{D}(k) = \quad (9)$$

$$\begin{bmatrix} \Phi(k) & \mathbf{0} & \mathbf{0} & \dots & \mathbf{0} & \mathbf{0} \\ \Phi(k) & \Phi(k+1) & \mathbf{0} & \dots & \mathbf{0} & \mathbf{0} \\ \vdots & \vdots & \ddots & \ddots & \ddots & \vdots \\ \Phi(k) & \Phi(k+1) & \vdots & \Phi(k+N_u-1) & \mathbf{0} & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \Phi(k) & \Phi(k+1) & \dots & \Phi(k+N_u-1) & \dots & \Phi(k+N-1) \end{bmatrix}_{N\times N},$$

where $\mathbf{Y}_N(k+1)$ denotes the N-step-ahead prediction vector of the system output, $\Delta\mathbf{U}_N(k)$ represents the predicted control input increment vector along the output prediction horizon $k = 1, 2, ..., N_u, ..., N$, while $\mathbf{I}_{r\times m}$ is an identity matrix and $\mathbf{0}_{r\times m}$ is a zero matrix.

Consequently, (5) can be rewritten in a general compact-form of N-step-ahead prediction equation as

$$\mathbf{Y}_N(k+1) = \mathbf{E}(k)\mathbf{y}(k) + \mathbf{D}(k)\Delta\mathbf{U}_N(k). \quad (10)$$

From (7), assuming that $\Delta\mathbf{u}(k+j-1) = \mathbf{0}$ if $j > N_u$, then the prediction equation (10) becomes

$$\mathbf{Y}_N(k+1) = \mathbf{E}(k)\mathbf{y}(k) + \mathbf{D}_1(k)\Delta\mathbf{U}_{N_u}(k), \quad (11)$$

where

$$\Delta \mathbf{U}_{N_u}(k) = [\Delta \mathbf{u}(k), \Delta \mathbf{u}(k+1), ..., \Delta \mathbf{u}(k+N_u-1)]^T, \tag{12}$$

$$\mathbf{D}_1(k) = \begin{bmatrix} \Phi(k) & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \Phi(k) & \Phi(k+1) & \mathbf{0} & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \Phi(k) & \Phi(k+1) & \dots & \Phi(k+N_u-1) \\ \vdots & \vdots & \dots & \vdots \\ \Phi(k) & \Phi(k+1) & \dots & \Phi(k+N_u-1) \end{bmatrix}_{N \times N_u} . \tag{13}$$

Based on the output prediction equation (11), calculation of the future control input increment vector $\Delta \mathbf{U}_{N_u}(k)$ as well as the current control input vector $\mathbf{u}(k)$ will be discussed in the next sections.

Parameter estimation and prediction

The unknown time-varying parameter matrices $\Phi(k), \Phi(k+1), ..., \Phi(k+N_u-1)$ in (13) could be estimated and predicted by using only the available system I/O data. To estimate the PJM parameters at current time $\Phi(k)$, this paper considers the RLSA [19] for estimation accuracy improvement. The other PJM matrices in the next instants $\Phi(k+1), \Phi(k+2), ..., \Phi(k+N_u-1)$ can be predicted according to the existing values $\hat{\Phi}(1), \hat{\Phi}(2), ..., \hat{\Phi}(k)$ by applying the multilevel hierarchical forecasting algorithm [20].
The RLS estimation method [19] can be applied to the CFDL model (2) to update the system parameters $\Phi(k)$ recursively. As result, the CFDL-RLS algorithm is obtained as

$$\mathbf{P}(k) = \mathbf{P}(k-1) - \mathbf{P}(k-1)\Delta \mathbf{u}(k-1) \tag{14}$$
$$\left[I + \Delta \mathbf{u}^T(k-1)\mathbf{P}(k-1)\Delta \mathbf{u}(k-1)\right]^{-1} \Delta \mathbf{u}^T(k-1)\mathbf{P}(k-1),$$
$$\mathbf{K}(k) = \mathbf{P}(k-1)\Delta \mathbf{u}(k-1)\left[I + \Delta \mathbf{u}^T(k-1)\mathbf{P}(k-1)\Delta \mathbf{u}(k-1)\right]^{-1}, \tag{15}$$
$$\hat{\Phi}(k) = \hat{\Phi}(k-1) + \mathbf{K}(k)\left[\Delta \mathbf{y}(k) - \hat{\Phi}(k-1)\Delta \mathbf{u}(k-1)\right], \tag{16}$$

where $\hat{\Phi}(1)$ denotes the initial PJM values, $\mathbf{P}(k), \mathbf{K}(k)$ are the unknown parameter matrices, and $\mathbf{P}(0)$ is any initial positive definite matrix $\mathbf{P}_0$.
To improve the performance of the least-squares algorithm, a modified RLSA [2] is considered and could be applied to the linearized data-based model (2) which results to

$$\mathbf{P}(k) = \mathbf{P}(k-1) - \mathbf{P}(k-1)\Delta \mathbf{u}(k-1) \tag{17}$$
$$\left[I + \Delta \mathbf{u}^T(k-1)\mathbf{P}(k-1)\Delta \mathbf{u}(k-1)\right]^{-1} \Delta \mathbf{u}^T(k-1)\mathbf{P}(k-1),$$
$$\hat{\Phi}(k) = \hat{\Phi}(k-1) + \mathbf{P}(k)\Delta \mathbf{u}(k-1) \tag{18}$$
$$\left[\Delta \mathbf{y}(k) - \hat{\Phi}(k-1)\Delta \mathbf{u}(k-1)\right] - \gamma \mathbf{P}(k)\left[\hat{\Phi}(k-1) - \hat{\Phi}(k-2)\right],$$

where $\gamma > 0$ is a constant parameter.
To predict the future PJM matrices $\Phi(k+1), \Phi(k+2), ..., \Phi(k+N_u-1)$ in (13), the available estimated values $\hat{\Phi}(1), \hat{\Phi}(2), ..., \hat{\Phi}(k)$ calculating in (17), (18) are used. In this contribution, the multilevel hierarchical forecasting method as presented in [20] is applied. As result, an autoregressive prediction model of the PJM in next step $(k+1)$ is denoted as

$$\hat{\Phi}(k+1) = \theta_1(k)\hat{\Phi}(k) + \theta_2(k)\hat{\Phi}(k-1) + \ldots + \theta_{n_p}(k)\hat{\Phi}(k-n_p+1), \tag{19}$$

where θ_i, $i = 1, 2, \ldots, n_p$ are the coefficients and $n_p = 2 \div 7$ as recommended in [14] indicates the fixed model order. Therefore, in general the prediction equation of the PJM can be written as

$$\hat{\Phi}(k+j) = \theta_1(k)\hat{\Phi}(k+j-1) + \theta_2(k)\hat{\Phi}(k+j-2) + \ldots + \theta_{n_p}(k)\hat{\Phi}(k+j-n_p), \tag{20}$$

where $j = 1, 2, ..., N_u - 1$. Let the following values

$$\theta(k) = \left[\theta_1(k), \theta_2(k), \ldots, \theta_{n_p}(k)\right]^T, \tag{21}$$
$$\hat{\Psi}(k-1) = \left[\hat{\Phi}(k-1), \hat{\Phi}(k-2), \ldots, \hat{\Phi}(k-n_p)\right]^T, \tag{22}$$
$$\hat{\Phi}(k) = \theta^T(k)\hat{\Psi}(k-1). \tag{23}$$

The unknown parameters $\theta_1(k), \theta_2(k), \ldots, \theta_{n_p}(k)$ in (19) and (20) can be computed by minimizing the following objective function [14]

$$J(\theta(k)) = \left\|\Phi(k) - \Psi(k-1)\theta^T(k)\right\|^2 + \delta\|\theta(k) - \theta(k-1)\|^2. \tag{24}$$

Differentiating function (24) with respect to $\theta(k)$ and letting it zero, hences the optimal parameters

$$\theta(k) = \theta(k-1) + \frac{\hat{\Psi}(k-1)\left[\hat{\Phi}(k) - \theta^T(k-1)\hat{\Psi}(k-1)\right]}{\delta + \left\|\hat{\Psi}(k-1)\right\|^2}, \tag{25}$$

where $\delta \in (0,1]$ is a designed positive constant. Based on the vector of parameters $\theta(k)$ in (21) which are recursively calculated in (25) and the old PJM values up to current step $\hat{\Phi}(1),\ldots,\hat{\Phi}(k)$, the upcoming PJM parameters at steps $j = 1,2,\ldots,N_u-1$ are predicted via (20).

MODEL-FREE ADAPTIVE PREDICTIVE CONTROL DESIGN

A model-free adaptive predictive controller is designed in this section. The proposed approach can be applied to vibration control of a class of mechanical flexible systems. By using the estimated and predicted system parameters $\hat{\Phi}(k),\hat{\Phi}(k+1),\ldots,\hat{\Phi}(k+N_u-1)$ as well as the predicted tracking errors $\mathbf{e}(k+1)$ within the output prediction horizon N, the required control input vector $\mathbf{u}(k)$ will be calculated to fulfill the initial control requirements.

Control input calculation

The future control input increment vector $\Delta\mathbf{U}_{N_u}(k)$ in (11) can be predicted along the control prediction horizon $k = 1,2,\ldots,N_u$. The control goal is to minimize the predicted output tracking errors between the future references $\mathbf{y}^d(k+i)$ and the predicted system outputs $\mathbf{y}(k+i)$ considering input energy limitation by introducing a weighting factor λ, where $i = 1,2,...,N$. The objective function of the control input increment vector ($\Delta\mathbf{u}$) is illustrated as

$$J(\Delta\mathbf{u}) = \sum_{i=1}^{N} \left\| \mathbf{y}^d(k+i) - \mathbf{y}(k+i) \right\|^2 + \lambda \sum_{j=0}^{N_u-1} \|\Delta\mathbf{u}(k+j)\|^2, \tag{26}$$

where $\lambda > 0$ is a constant parameter which is added to restrict the change rate of the future control inputs. The desired system outputs $\mathbf{y}^d(k+i)$ in (26) along the output prediction horizon N can be written as

$$\mathbf{Y}_N^d(k+1) = \left[\mathbf{y}^d(k+1),\ldots,\mathbf{y}^d(k+N_u),\ldots,\mathbf{y}^d(k+N)\right]^T. \tag{27}$$

By substituting (6), (12), and (27) into (26), the above cost function can be rewritten as

$$J(\Delta\mathbf{U}) = \left[\mathbf{Y}_N^d(k+1) - \mathbf{Y}_N(k+1)\right]^T \left[\mathbf{Y}_N^d(k+1) - \mathbf{Y}_N(k+1)\right] \tag{28}$$
$$+ \lambda \Delta\mathbf{U}_{N_u}{}^T(k)\Delta\mathbf{U}_{N_u}(k).$$

The future system outputs $\mathbf{Y}_N(k+1)$ are calculated by using the general compact-form prediction model (11). Therefore, the above function can be expressed as

$$\begin{aligned} J(\Delta\mathbf{U}) = & \left[\mathbf{Y}_N^d(k+1) - \mathbf{E}(k)\mathbf{y}(k) - \mathbf{D}_1(k)\Delta\mathbf{U}_{N_u}(k)\right]^2 \\ & + \lambda \Delta\mathbf{U}^T{}_{N_u}(k)\Delta\mathbf{U}_{N_u}(k). \end{aligned} \tag{29}$$

Solving the optimal problem by differentiating the function (29) with respect to $\Delta\mathbf{U}_{N_u}(k)$ and letting it zero, yields

$$\begin{aligned} \frac{\partial J}{\partial \Delta\mathbf{U}_{N_u}(k)} = & 2\left[\mathbf{Y}_N^d(k+1) - \mathbf{E}(k)\mathbf{y}(k) - \mathbf{D}_1(k)\Delta\mathbf{U}_{N_u}(k)\right] \\ & \left(-\mathbf{D}^T{}_1(k)\right) + 2\lambda\Delta\mathbf{U}_{N_u}(k) = 0. \end{aligned} \tag{30}$$

Finally, the predicted control input increment vector can be determined as

$$\begin{aligned} & \Delta\mathbf{U}_{N_u}(k) = \\ & \left[\mathbf{D}^T{}_1(k)\mathbf{D}_1(k) + \lambda\mathbf{I}\right]^{-1}\mathbf{D}^T{}_1(k)\left[\mathbf{Y}_N^d(k+1) - \mathbf{E}(k)\mathbf{y}(k)\right], \end{aligned} \tag{31}$$

in which the unknown time-varying parameter matrix $\mathbf{D}_1(k)$ can be estimated and predicted using the discussed algorithms (17), (18), (20), and (25). Then, the current control input vector $\mathbf{u}(k)$ is computed by applying the receding horizon principle [2] as

$$\mathbf{u}(k) = \mathbf{u}(k-1) + \mathbf{g}^T\Delta\mathbf{U}_{N_u}(k), \tag{32}$$

where $\mathbf{g} = [\mathbf{I}_{r\times m}, \mathbf{0}_{r\times m}, \ldots, \mathbf{0}_{r\times m}]^T$, with r,m denoting the number of system outputs and control inputs, respectively.

Steps for model-free controller design

The proposed method can be applied to a class of unknown MIMO systems in which the system I/O data can be directly computed or measured. A general MFAPC scheme of a MIMO crane represented as a multivariable system is shown in Fig.1. To design a model-free adaptive predictive-based control program, the following steps have to be implemented:

1. Based on the CFDL data model and the available I/O information from the controlled system, the unknown PJM parameters at current step $\hat{\Phi}(k)$ are estimated and updated repeatedly by using the modified RLSA (17), (18). According to [2] and based on assumption 3, to improve the ability in tracking parameters, a reset condition is considered as

$$\begin{aligned} \hat{\phi}_{ii}(k) = \hat{\phi}_{ii}(1) \ if \ \left|\hat{\phi}_{ii}(k)\right| < c_2 \ or \ \left|\hat{\phi}_{ii}(k)\right| > \alpha c_2 \\ or \ sign(\hat{\phi}_{ii}(k)) \neq sign(\hat{\phi}_{ii}(1)), \end{aligned} \tag{33}$$

$$\hat{\phi}_{ij}(k) = \hat{\phi}_{ij}(1) \ if \ \left|\hat{\phi}_{ij}(k)\right| > c_1 \quad or \ sign(\hat{\phi}_{ij}(k)) \neq sign(\hat{\phi}_{ij}(1)), \tag{34}$$

where $\hat{\phi}_{ii}(1), \hat{\phi}_{ij}(1)$ are the initial values of the PJM, with $i, j = 1, 2, \ldots, n; i \neq j$.

2. Using the current updated PJM $\hat{\Phi}(k)$ as well as the existing values from previous steps $\hat{\Phi}(1), \hat{\Phi}(2), ..., \hat{\Phi}(k-1)$, the unknown parameters $\theta(k)$ can be determined via (25). As discussed in [14], the below condition has to be fulfilled

$$\theta(k) = \theta(1) \ if \ \|\theta(k)\| \geq M, \tag{35}$$

where M is a positive constant and $\theta(1)$ is the initial vector-value of $\theta(k)$.

3. The calculated parameters $\theta(k)$ are used to predict the future pseudo-jacobian matrices $\hat{\Phi}(k+j)$ with $j = 1, 2, ..., N_u - 1$, that means the parameter matrix $\mathbf{D}_1(k)$ is completely defined by (13). To improve the tracking ability of the PJM prediction algorithm, another reset condition [2] has to be realized as

$$\hat{\phi}_{ii}(k+j) = \hat{\phi}_{ii}(1) \ if \ \left|\hat{\phi}_{ii}(k+j)\right| < c_2 \ or \ \left|\hat{\phi}_{ii}(k+j)\right| > \alpha c_2 \quad or \ sign(\hat{\phi}_{ii}(k+j)) \neq sign(\hat{\phi}_{ii}(1)), \tag{36}$$

$$\hat{\phi}_{ij}(k+j) = \hat{\phi}_{ij}(1) \ if \ \left|\hat{\phi}_{ij}(k)\right| > c_1 \quad or \ sign(\hat{\phi}_{ij}(k+j)) \neq sign(\hat{\phi}_{ij}(1)). \tag{37}$$

4. By using the estimated and predicted PJM parameters $\mathbf{D}_1(k)$ and the output tracking errors $\mathbf{e}(k+1)$, the control input increment vector $\Delta\mathbf{U}_{N_u}(k)$ as well as the required control input values are defined according to (31), (32). Finally, the upcoming outputs $\mathbf{y}(k+1)$ are computed or measured again and the given process is implemented repeatedly.

VIBRATION CONTROL EXAMPLE

In this section, the discussed MFAPC program is applied to reduce free vibrations of a flexible crane. The elastic ship-mounted crane with the "Maryland Rigging" has been developed in [21] for cargo transportation in open sea. Due to the effects of wave motion and wind force represented as unknown external disturbances together with the excitation from non-zero initial position of the payload, large oscillations could appear which might lead to dangerous situations of the crane operation. Consequently, the crane normally becomes unstable if no controller

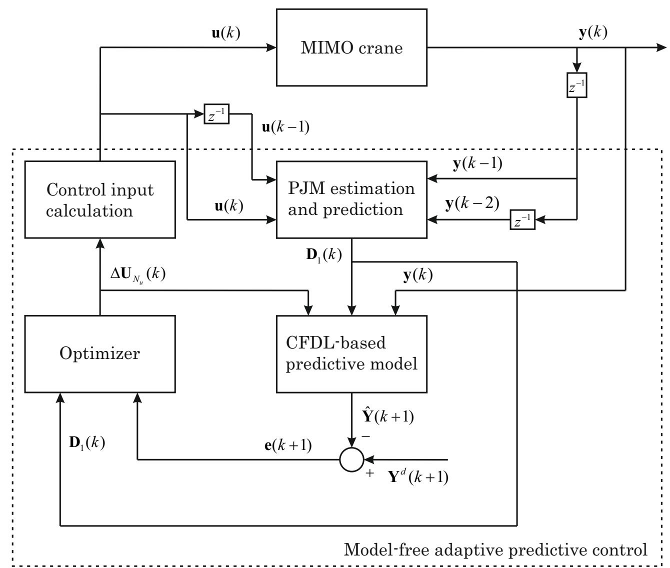

FIGURE 1. GENERAL MODEL-FREE ADAPTIVE PREDICTIVE CONTROL SCHEME OF A MIMO CRANE

is used. The control goal is to reduce the vibrations of the elastic part of the boom (at node 6) and the payload m_2 (Fig.2). First, the crane configuration and the linearized state-space model are reviewed briefly. The model is simulated only to acquire I/O data for model-free control design. Then, controller parameters as well as simulation results are illustrated with comparisons to other conventional approaches.

Introduction to the elastic crane

The configuration of the ship-mounted crane is shown in Fig.2. The boom of the crane is divided into two parts: elastic part (AB) and rigid part (BC) in which the moment M_A is assumed to be applied to the lower point A (at node 1) of the boom [21]. The control purpose is to suppress the vibrations of the elastic part AB represented as the angle θ_6 (at node 6) and the angular displacements of the payload cable (ϕ_2) and the upper cable (α_2). The system output vector is denoted in discrete-time as

$$\mathbf{y}(k) = [\Delta\theta_6(k) \ \Delta\alpha_2(k) \ \Delta\phi_2(k)]^T. \tag{38}$$

Three control input variables are defined to fulfill the control requirements namely the displacements of the luff angle ($\Delta\rho$), the total length of the upper cable (ΔL with $L = L_1 + L_2$), and the lower suspension point position (ΔD) of the upper cable (Fig.2). The vector of control inputs is written as

$$\mathbf{u}(k) = [\Delta\rho(k) \ \Delta L(k) \ \Delta D(k)]^T. \tag{39}$$

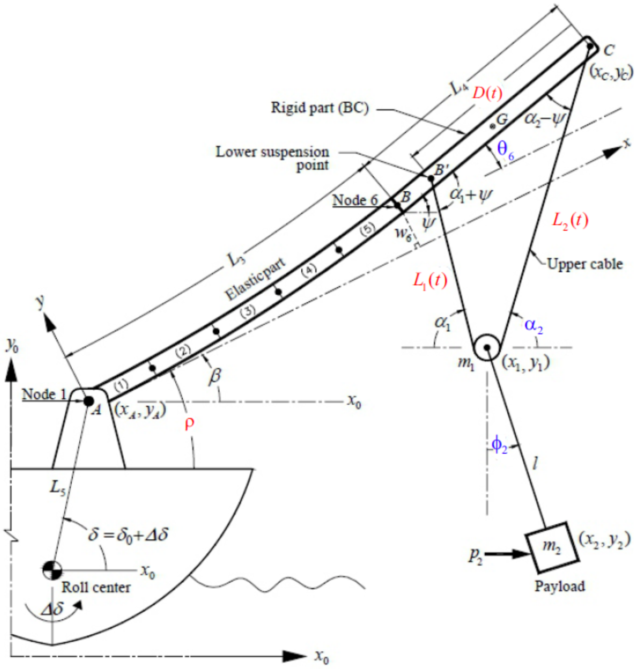

FIGURE 2. CONFIGURATION OF THE ELASTIC SHIP-MOUNTED CRANE WITH THE "MARYLAND RIGGING" [21]

To estimate and predict the unknown time-varying parameters $\Phi(k), \Phi(k+1), \ldots, \Phi(k+N_u-1)$ in (13), the I/O data of the crane up to step $(k-1)$ has to be calculated. For this purpose, the linearized state-space model which is taken from the crane motion equations [21] needs to be transformed into discrete-time domain as follows

$$\mathbf{z}(k+1) = \mathbf{G}\mathbf{z}(k) + \mathbf{H}\mathbf{u}(k) + \mathbf{J}\Delta\delta(k) + \mathbf{Q}p_2(k), \qquad (40)$$
$$\mathbf{y}(k) = \mathbf{C}\mathbf{z}(k) + \mathbf{D}\mathbf{u}(k) + \mathbf{F}\Delta\delta(k),$$

where $\mathbf{z}$ denotes the system state vector. Here $\mathbf{G}, \mathbf{H}$ are the corresponding system and input matrices, respectively; whereas the system output and the input direct transmission matrices are indicated as $\mathbf{C}$ and $\mathbf{D}$, correspondingly. The disturbance matrices are represented as $\mathbf{J}$ due to ship rolling ($\Delta\delta$), and $\mathbf{Q}$ due to wind force (p_2). The disturbance direct transmission matrix $\mathbf{F}$ is resulted by the sea motion effects. In Tab.1, several initial parameters of the crane are given.

Tracking control performance

The modified MFAPC requires the estimated parameters $\hat{\Phi}(k)$ which are obtained from (17), (18) and the predicted PJM $\hat{\Phi}(k+1), \hat{\Phi}(k+2), \ldots, \hat{\Phi}(k+N_u-1)$ which are calculated via (20), (25). The required control input values are realized by using (31), (32). In this contribution, the tracking control

TABLE 1. INITIAL PARAMETERS OF THE ELASTIC SHIP-MOUNTED CRANE

Parameter	Meaning	Value [Unit]
β_0	Orientation of the boom axis	$\pi/4$ [rad]
D_0	Low-point suspension cable	0.55 [m]
L_0	Length of the upper cable	1.60 [m]
m_1	Mass of the pulley	0.50 [kg]
m_2	Mass of the payload	5.0 [kg]
$\dot{\phi}_{20}$	Initial payload angular velocity	5.0 [rad/s]

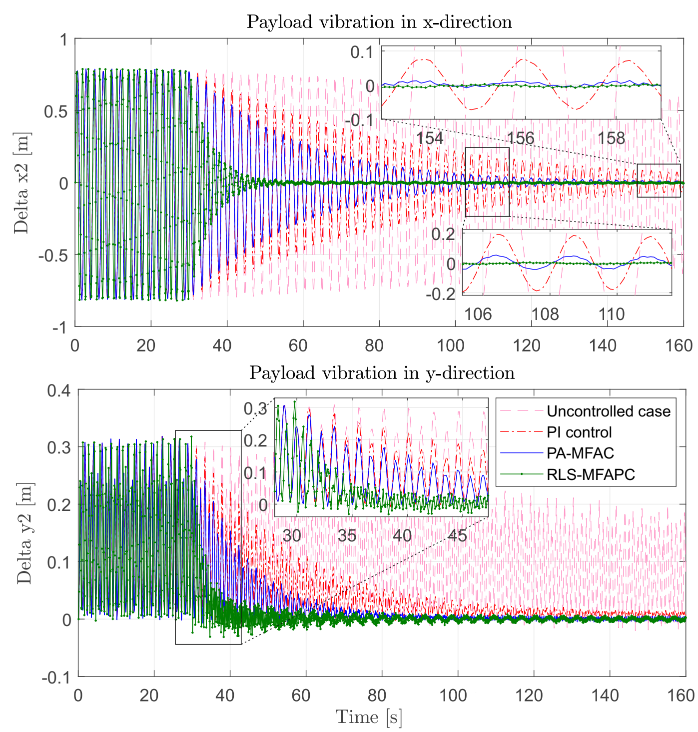

FIGURE 3. COMPARISON OF VIBRATION CONTROL WITH RESPECT TO THE PAYLOAD POSITION Δx_2 AND Δy_2

ability of the designed controllers is evaluated in case of without considering external disturbance effects, that means $\Delta\delta(k) = p_2(k) = 0$. However, by consideration of non-zero initial excitation to the payload ($\dot{\phi}_{20} = 5.0$ [rad/s] in Tab.1), there are still unexpected oscillations in the system. The recursive least-squares-based model-free adaptive predictive control (RLS-MFAPC) results are shown and compared with that of the projection algorithm-based MFAC (PA-MFAC) and standard

PI control. In Fig.3, the comparison of vibration control with respect to the payload position in x- and y-direction denoted as Δx_2 and Δy_2 is illustrated. The control part of the simulation starts from $t = 30$ $[s]$. It can be seen that the RLS-MFAPC (green lines) has better tracking control performance with respect to smaller control error amplitudes compared to the PA-MFAC (blue lines) and PI control (red-dot lines). It takes approximately 10 $[s]$ to reduce the oscillation of the payload position in case of applying the modified model-free controller. To observe the system dynamic behaviors due to non-zero initial condition of the payload ($\dot{\phi}_{20}$), the results in uncontrolled situation are also given (pink-dash lines). The designed parameters of the RLS-MFAPC and PI controller are given in Tab.2. In addition, the output control results regarding the upper cable ($\Delta\alpha_2$) and the payload cable ($\Delta\phi_2$) are described in Fig.4. It is clear that the angular displacements are reduced significantly from $\Delta\alpha_2 = 30$ [deg] and $\Delta\phi_2 = 50$ [deg] to nearly zero at the end of the simulation when using the RLS-MFAPC (green lines). Therefore, the modified model-free control results are much better than those of the conventional approaches.

Control input energy-based evaluation

A method to evaluate control efficiency is using the relationship between control input energy $\int \mathbf{u}^2(t)dt$ and output tracking error $\int \mathbf{e}^2(t)dt$ within a suitable length of time $T = [t_1, t_2]$ [22]. By varying controller parameters, different trajectories (P_K) of the required control input signals $\mathbf{u} = [\Delta L, \Delta D]$ as well as the payload tracking control errors $\mathbf{e} = [\Delta x_2, \Delta y_2]$ are obtained

$$P_K = \left[\int_{t_1}^{t_2} \mathbf{u}^2(t)dt, \int_{t_1}^{t_2} \mathbf{e}^2(t)dt \right]_K, \tag{41}$$

where $K = [\lambda, \delta, K_p, K_i]$ is a set of controller gains of the RLS-MFAPC, PA-MFAC, and PI controller. Here $\lambda > 0$ is an important parameter which can be chosen suitably to improve the modified model-free control performance via (31). In Fig.5, the control performance evaluation with respect to the criteria (41) within a specified interval length of time $T_1 = [30, 160]$ $[s]$ (or transient phase) is presented. It can be observed that the trajectory P_K of the RLS-MFAPC (black dots) is closer to the origin $(0,0)$ when varying the controller parameters K, that means the proposed control approach is more robust in comparison with the conventional PA-MFAC (blue dots) and PI control (red dots). To evaluate the control performance in stationary phase with the simulation time $T_2 = [130, 160]$ $[s]$, the results of trajectory of the three discussed controllers are depicted in Fig.6. Generally speaking, the RLS-MFAPC indicates better control performance regarding to smaller tracking control error amplitudes. However, the proposed controller still requires more control input energy compared to the other traditional methods.

TABLE 2. DESIGN PARAMETERS OF THE RLS-MFAPC AND PI CONTROLLER

Parameter	Meaning	Value [Unit]
λ	Constant weighting factor	75 [-]
ε	Small positive constant	10^{-5} [-]
δ	Designed positive constant	0.75 [-]
N	Prediction horizon of the output	6 [-]
N_u	Control input prediction horizon	2 [-]
γ	Constant design parameter	0.75 [-]
n_p	Prediction model coefficient	2 [-]
M	Designed positive constant	5 [-]
K_p	PI control parameter	0.002 [-]
K_i	PI control parameter	0.1 [-]

CONCLUSION

This paper introduces a modified online parameter estimation method by applying the recursive least-squares algorithm to improve parameter estimation accuracy. The estimated and predicted system parameters are used to design an improve model-free adaptive controller for a class of unknown MIMO systems. To reduce unexpected oscillations in mechanical flexible systems, the proposed method has been applied to an elastic ship-mounted crane. The simulation results show that the vibrations of the elastic boom and the payload are reduced considerably, and better control performance is observed when using the modified controller in comparison with traditional approaches.

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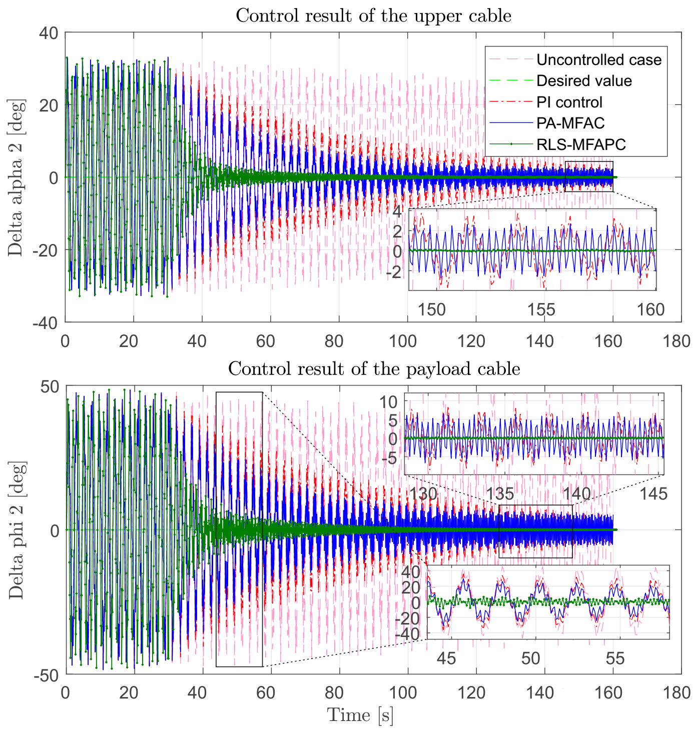

FIGURE 4. COMPARISON OF VIBRATION CONTROL WITH RESPECT TO THE OUTPUT VALUES $\Delta\alpha_2$ AND $\Delta\phi_2$

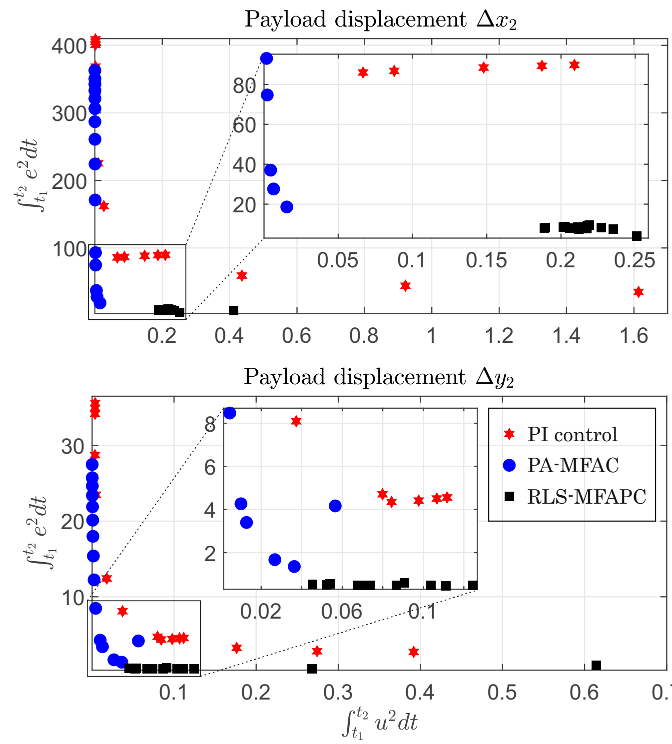

FIGURE 5. CONTROL PERFORMANCE EVALUATION ACCORDING TO THE CRITERIA (41) WITHIN $T_1 = [30, 160]$ $[s]$

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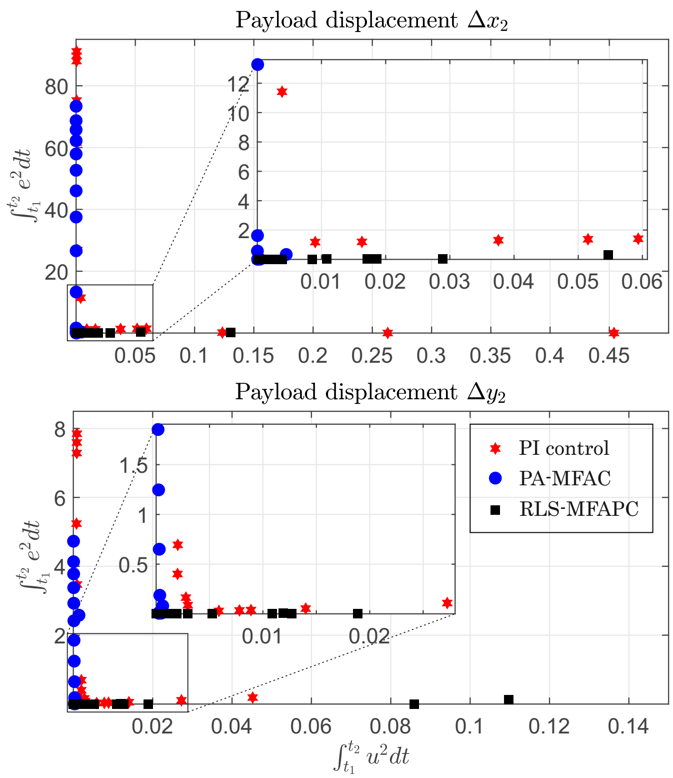

FIGURE 6. CONTROL PERFORMANCE EVALUATION ACCORDING TO THE CRITERIA (41) WITHIN $T_2 = [130, 160]$ $[s]$

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