Intelligent Control of Hydraulic Excavators Based on Data-Driven GPC and High-Order Fully Actuated Systems

Xin Wen[1], Zhe Guan[1,2], Kuo Chen[1], Changchun Hua[1]

1. School of Electrical Engineering, Yanshan University, Qinhuangdao 066004, China

2. Hebei Key Laboratory of Industrial Computer Control Engineering, Qinhuangdao 066004, China
E-mail: guan@ysu.edu.cn; wenxin@stumail.ysu.edu.cn; ck@stumail.ysu.edu.cn; cch@ysu.edu.cn

Abstract: This paper proposes an intelligent control approach based on data-driven generalized predictive control (DD-GPC), which is based on a high-order fully actuated (HOFA) system model and aims to solve the difficult problems of parameter uncertainties, strong nonlinearities, and significant time delays in the hydraulic excavator system. First, a generalized predictive controller is designed to compensate for the time delay of the system. Then, the GPC controller parameters are computed online using data-driven control theory within the framework of a HOFA system model to improve controller performance without the need for a comprehensive global mathematical model. Finally, an error feedback mechanism is introduced into the future reference value to improve the responsiveness of the system. The simulation results of the hydraulic excavator grading operation proved the superiority and effectiveness of the proposed method.

Key Words: data-driven, generalized predictive control, hydraulic excavator, time delay, high-order fully actuated systems, error feedback

1 Introduction

Construction machinery plays a pivotal role in China's economic development, which is an important part of the equipment manufacturing industry [1]. In recent years, with the development of science and technology and industrial change, construction machinery is accelerating the formation of new quality productivity. Among them, hydraulic excavators play a vital role in infrastructure, excavation, and mining. However, traditional hydraulic excavators have a low degree of intelligence, poor flexibility, and high operating difficulty [2], and excavator operators need to have rich operating experience to efficiently complete specific operational tasks. These problems seriously restrict the production quality and construction efficiency, so it is of great practical significance to realize the intelligent control of hydraulic excavators.

A major challenge for intelligent excavator control is the unknown delays inherent in hydraulic systems. To address delay control, reference [3] proposed a controller that integrates Time Delay Control [4] with Terminal Sliding Mode Control [5], which compensates for the nonlinear as well as the dynamic characteristics of the excavator system through time delay estimation. However, this approach does not consider the effect of parameter uncertainty. In contrast, the Generalized Predictive Control (GPC) algorithm [6] employs output prediction, roll optimization, and feedback correction to have the effect of solving the system delay and model order problems. Experimental studies [7] have shown that GPC maintains robust control performance even when the model parameters are uncertain, but its model-based nature requires accurate mathematical modeling, which is a challenging task for complex excavator dynamics.

Excavator systems have strong nonlinearities and parameter uncertainties, and it is difficult to obtain accurate excavator dynamics models based on methods such as first principles and system identification. In response, the theory of data-driven control [8] has been proposed, where only input and output data are required to design a controller without the need for an explicit system model. For instance, reference [9] proposed a data-driven framework for mining trajectory planning based on deep learning, while reference [10] developed a hybrid approach that combines an expert knowledge-based white-box model with a black-box neural network model to enhance system stability. In addition, reference [11] proposed a data-driven control system, which dynamically adjusts the PID parameters through real-time data analysis to realize precise swing control.

In addition to these challenges, the coupling of excavator hydraulic systems stems from a single pump supplying hydraulic fluid patterns to multiple actuators [12], which makes control more complex. Traditional decoupling-based nonlinear approaches may disrupt the inherent dynamics of the system, therefore degrading control performance and complicating the application of data-driven techniques. In contrast, the theory of higher-order fully actuated system proposed by Duan [13-15] provides a promising approach whereby complex nonlinear dynamics can be transformed into more tractable forms.

According to the HOFA system method [16], most of the systems can be described as high-order fully actuated control systems. In subsequent research, this framework was extended to nonlinear systems and adaptive control. For instance, in the literature [17], a system was transformed into a HOFA system and combined with an adaptive control strategy to achieve accurate trajectory tracking within a specified time frame while simplifying the design process and improving the control performance. However, few studies combining data-driven control with HOFA system have been identified. Based on the above, this paper proposes a data-driven GPC control method based on HOFA system and also considers a composite operation situation that

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requires coordinated movements of the excavator actuators. This enables the excavator to be intelligently controlled under complex operating conditions and improves operational efficiency.

The main contributions of this paper are summarized as follows:

(1) In this paper, the time delay problem is considered and a compensation strategy based on GPC is designed to effectively improve the control accuracy and dynamic response performance.

(2) A data-driven control approach is used to calculate GPC controller parameters online within the framework of a HOFA system to avoid relying on an accurate global mathematical model and to enhance the adaptability and robustness of the controller.

(3) The error feedback mechanism is introduced in the future reference value prediction to dynamically adjust the control strategy, which significantly improves the tracking speed and anti-interference ability of the system.

2 Problem Description

Hydraulic systems in excavator actuators have strong nonlinearities and parameter uncertainties, making it very difficult to obtain accurate models. Therefore, the system can be represented as a Single-Input Single-Output (SISO) nonlinear fully actuated system as follows:

$$y(t) = f(\phi(t-1)) + \xi(t) \tag{1}$$

Here $y(t)$, $f(\cdot)$, and $\xi(t)$ represent the system output, a nonlinear function, and Gaussian white noise with a mean of zero and a variance of σ^2, respectively. Moreover, $\phi(t-1)$ is referred to as the information vector, which is defined as follows:

$$\begin{aligned}\phi(t-1) :=& [y(t-1),\ \ldots,\ y(t-n_y),\\ & u(t-d-1),\ \ldots,\ u(t-d-n_u)]\end{aligned} \tag{2}$$

$u(t)$ and d denote the control input and the system time delay, respectively. Additionally, n_y and n_u represent the orders of the system output and the control input, respectively.

The Generalized Predictive Control (GPC) employs the following Controlled Auto-Regressive Integrated Moving Average Model (CARIMA) for implementation:

$$A(z^{-1})y(t) = z^{-(d+1)}B(z^{-1})u(t) + \frac{\xi(t)}{\Delta} \tag{3}$$

Here z^{-1} is the backward shift operator. Specifically, $z^{-1}y(t) = y(t-1)$ denotes shifting the signal $y(t)$ backward by one time unit, and Δ denotes the difference operator, defined as $\Delta := 1 - z^{-1}$. $A(z^{-1})$ and $B(z^{-1})$ are polynomials with the following expressions:

$$A(z^{-1}) = 1 + a_1 z^{-1} + \cdots + a_{n_y} z^{-n_y} \tag{4}$$

$$B(z^{-1}) = b_0 + b_1 z^{-1} + \cdots + b_{n_u} z^{-n_u} \tag{5}$$

The DD-GPC method proposed in this paper is implemented as follows:

First, offline data from the control system is collected to construct an initial database. Second, according to the data-driven control theory, the distance between the current time information vector and the information vector in the database is calculated, and the neighboring data is selected. Then, the polynomial parameters are recalculated using a linear weighted average method, and the parameters of the GPC controller are updated online with a set learning rate, and the database is updated. Finally, the control input $u(t)$ for the excavator system is computed by the GPC controller. The structural diagram of DD-GPC is shown in Fig.1.

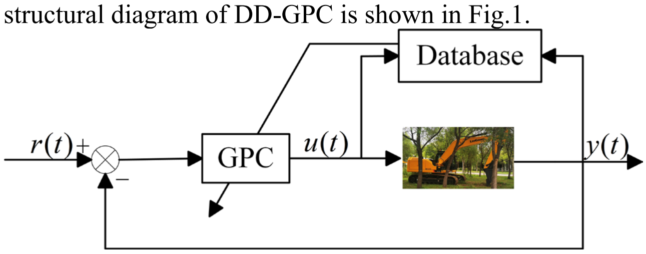

Fig. 1 Block schematic for the DD-GPC

3 Data-driven Generalized Predictive Control

3.1 GPC Controller Design

The GPC uses a weighted performance metric towards output error and control increment, which is expressed as follows:

$$\begin{aligned}J = E\Bigg[&\sum_{j=1}^{N}\{y(t+d+j) - r(t+d+j)\}^2 + \\ &\sum_{j=1}^{N}\lambda(j)\{\Delta u(t+j+1)\}^2\Bigg]\end{aligned} \tag{6}$$

where $E(\cdot)$ represents the desired value, $[1, N]$ denotes the control horizon and prediction horizon, $r(t)$ is the reference value, and $\lambda(j)$ is the specified weighting sequence.

Since the reference value of the hydraulic excavator changes over time during operation, it is necessary to introduce a current error feedback term $e(t)$ into the future reference value in order to achieve good control performance. The reference value is defined as follows:

$$r(t+j) = \alpha y(t+j-1) + (1-\alpha)r(t) + K_e e(t) \tag{7}$$

where α denotes the output smoothing factor, $e(t) = r(t) - y(t)$ denotes the deviation of the system output from the reference value, and K_e is the error weighting factor. The smoothing factor is used to control the speed of response of the control system output, ensuring a smooth transition to the setpoint. Meanwhile, the introduction of the error feedback mechanism improves the dynamic response performance of the system and enables it to track the reference signal quickly. When large deviations occur, this mechanism has a moderating effect and accelerates the convergence of the system to the target state.

In order to derive the output $y(t+j)$ predicted in step j, the following Diophantine equation is introduced into Equation (3):

$$\begin{aligned}&1 = \Delta A(z^{-1})E_j(z^{-1}) + z^{-j}F_j(z^{-1})\\ &E_j(z^{-1})B(z^{-1}) = R_j(z^{-1}) + z^{-j}S_j(z^{-1})\end{aligned} \tag{8}$$

which

$$\begin{aligned}&E_j(z^{-1}) = 1 + e_1 z^{-1} + \cdots + e_{j-1}z^{-(j-1)}\\ &F_j(z^{-1}) = f_0^j + f_1^j z^{-1} + \cdots + f_{n_y}^j z^{-n_y}\\ &R_j(z^{-1}) = r_0 + r_1 z^{-1} + \cdots + r_{j-1}z^{-(j-1)}\\ &S_j(z^{-1}) = s_0^j + s_1^j z^{-1} + \cdots + s_{n_u-1}^j z^{-(n_u-1)}\end{aligned} \tag{9}$$

Multiplying both sides of Equation (3) by $E_j(z^{-1})$ and substituting into Equation (8) gives the following equation:

$$y(t+j)=F_j(z^{-1})y(t)+E_j(z^{-1})\xi(t+j)+ \\ E_j(z^{-1})B(z^{-1})\Delta u(t+j-1) \tag{10}$$

Let $E_j(z^{-1})B(z^{-1})=G_j(z^{-1})$, and the above equation can be rewritten as:

$$y(t+j)=G_j(z^{-1})\Delta u(t+j-1)+F_j(z^{-1})y(t) \tag{11}$$

Using Equation (8), rewrite Equation (11) as:

$$y(t+j)=F_j(z^{-1})y(t)+S_j(z^{-1})\Delta u(t-1)+ \\ R_j(z^{-1})\Delta u(t+j-1) \tag{12}$$

Then, the above equation is expressed in vector form as:

$$\tilde{\boldsymbol{y}}=\boldsymbol{R}\tilde{\boldsymbol{u}}+\boldsymbol{F}y(t)+\boldsymbol{S}\Delta u(t-1) \tag{13}$$

which

$$\tilde{\boldsymbol{y}}=\left[\tilde{y}(t+1),\tilde{y}(t+2),\cdots,\tilde{y}(t+N)\right]^{\mathrm{T}}$$

$$\tilde{\boldsymbol{u}}=\left[\Delta u(t),\Delta u(t+1),\cdots,\Delta u(t+N-1)\right]$$

$$\boldsymbol{F}=\left[F_1,F_2,\cdots,F_N\right]^{\mathrm{T}}$$

$$\boldsymbol{S}=\left[S_1,S_2,\cdots,S_N\right]^{\mathrm{T}}$$

Specifically, matrix $\boldsymbol{R}$ is denoted as:

$$\boldsymbol{R}=\begin{bmatrix} r_0 & 0 & \cdots & 0 \\ r_1 & r_0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ r_{N-1} & r_{N-2} & \cdots & r_0 \end{bmatrix} \tag{14}$$

By taking the partial derivative of $\tilde{\boldsymbol{u}}$ and minimizing J, the following control sequence is obtained:

$$\tilde{\boldsymbol{u}}=(\boldsymbol{R}^{\mathrm{T}}\boldsymbol{R}+\Lambda)^{-1}\boldsymbol{R}^{\mathrm{T}}(r-\boldsymbol{F}y(t)-\boldsymbol{S}\Delta u(t-1)) \tag{15}$$

Among them, the first element of vector $\tilde{u}$ is $\Delta u(t)$, and the control input $u(t)$ can be derived as:

$$u(t)=u(t-1)+\left[1,0,\cdots,0\right]\tilde{\boldsymbol{u}} \tag{16}$$

3.2 Data-Driven Control Theory

By Equation (11), it can be seen that when $j=1$, the one-step-ahead predicted output are:

$$\tilde{y}(t+1)=F_1(z^{-1})y(t)+G_1(z^{-1})\Delta u(t) \tag{17}$$

This shows the relationship between the single-step prediction outputs and the polynomials $F_1(z^{-1})$ and $G_1(z^{-1})$. In the existing work [18], the determined polynomial parameters are generally kept constant, which may lead to performance degradation when the system characteristics change or exhibit strong nonlinearities. Therefore, in order to solve the above problems, data-driven theory is introduced on the basis of GPC control algorithm.

Data-driven theory relies on the input and output data of the system, which operates in an online manner. This means that the polynomials $F_1(z^{-1},t)$ and $G_1(z^{-1},t)$ will be updated online according to the database. The data-driven approach is illustrated by analyzing GPC parameters $F_1(z^{-1},t)$ and $G_1(z^{-1},t)$. Rewrite the above Equation (17) in the form of an information vector as:

$$\tilde{y}(t+1)=\phi^{\mathrm{T}}(t)\theta(t) \tag{18}$$

where $F_1(z^{-1},t)$ and $G_1(z^{-1},t)$ are components in $\theta(t)$ and

$$\phi(t-1):=\left[y(t-1),\cdots,y(t-n_y), \\ \Delta u(t-1),\cdots,\Delta u(t-n_u)\right] \tag{19}$$

Before introducing the data-driven method, it is necessary to introduce the query vector $\bar{\phi}(t)$ at the current moment, which is defined as follows:

$$\bar{\phi}(t):=\left[r(t+1),y(t),\cdots,y(t-n_y+1), \\ \Delta u(t-1),\cdots,\Delta u(t-n_u)\right] \tag{20}$$

where $r(t+1)$ is the reference signal at time $(t+1)$.

The specific process of the data-driven method is as follows.

Step 1: Generate the initial database.

Data-driven control theory requires data to support it, so the initial database consists of offline data collected from the excavator. Typically, unit step signals can be used as the system input to collect corresponding input and output data. For the excavator system, voltage values can be manually assigned as inputs to control the hydraulic cylinders to perform extension and retraction actions, and then sensors can collect the offline data from the excavator. Next, the initial collected offline dataset is used in conjunction with Equation (17) to determine its polynomial parameters, i.e., the coefficients of $F_1(z^{-1})$ and $G_1(z^{-1})$. Then, the input data, output data, reference signal, $F_1(z^{-1})$ and $G_1(z^{-1})$ are stored in the database defined as follows:

$$\Phi(q):=\left[\bar{\phi}(q),\theta(q)\right],q=1,2,\cdots,N_0 \tag{21}$$

where N_0 is the number of datasets in the initial database.

Specifically, in the initial stage, each set of parameters $F_1(z^{-1})$ and $G_1(z^{-1})$ remains unchanged.

Step 2: Calculate distances and select neighboring data.

The distance between the query vector $\bar{\phi}(t)$ and the information vector $\bar{\phi}(q)$ is calculated using the L_1-norm.

$$\Upsilon(\bar{\phi}(t),\bar{\phi}(q))=\sum_{l=1}^{n_y+n_u+1}\left|\frac{\bar{\phi}_l(t)-\bar{\phi}_l(q)}{\max\bar{\phi}_l(m)-\min\bar{\phi}_l(m)}\right|, \\ j=1,2,\cdots,N_t \tag{22}$$

Here, N_t is the dimension of the database, $\bar{\phi}_l(t)$ is the lth element of the query at the current moment, and $\bar{\phi}_l(q)$ is the qth element of the lth information vector. Furthermore, $\max\bar{\phi}_l(m)$ is the maximum element among the lth elements of all information vectors, and similarly, $\min\bar{\phi}_l(m)$ is the minimum element among the lth elements. Therefore, the database sorts the calculated distances in ascending order and then selects the neighboring data in Group N_e.

Step 3: Recalculate the initial polynomial parameters.

In this step, using the selected N_e sets of neighboring data, the parameters $F_1(z^{-1},t)$ and $G_1(z^{-1},t)$ are recalculated online using a linear weighted average [19], as shown below:

$$\theta^{old}(t)=\sum_{i=1}^{N_e}\omega_i\theta(i),\sum_{i=1}^{N_e}\omega_i=1 \tag{23}$$

which

$$\omega_i=\frac{\exp(-\Upsilon_i)}{\sum_{i=1}^{N_e}\exp(-\Upsilon_i)} \tag{24}$$

Step 4: Parameter adjustment.

Finally, the obtained parameters $\theta^{old}(t)$ are updated online using the steepest descent method to obtain satisfactory performance. The parameter adjustment formula is defined as follows:

$$\theta^{new}(t) = \theta^{old}(t) - \eta \frac{\partial J(t+1)}{\partial \theta(t)} \quad (25)$$

where η denotes the parameter learning rate and $J(t+1)$ denotes the prediction error, which is defined as:

$$J(t+1) := \frac{1}{2}\varepsilon(t+1)^2 \quad (26)$$

$$\varepsilon(t+1) := y(t+1) - \tilde{y}(t+1) \quad (27)$$

4 Simulation Results

In order to demonstrate the effectiveness of the proposed control method in dealing with nonlinearities and time delays, as well as the superiority of the DD-GPC method, this section simulates the leveling operation of the bucket tip of a hydraulic excavator. The performance of three different controllers in tracking the displacements of the hydraulic cylinders of the boom and arm hydraulic cylinders under the same time delay conditions and the grading effect of the excavator when it performs a compound operation are compared. The effectiveness of the proposed method is verified through numerical simulations.

First, consider the mathematical model of the excavator's boom hydraulic control system in the following form [20]:

$$\frac{\omega_h^2 K_a K_b K_q}{\tau A} U = y^{(4)} + (2\xi_h \omega_h + \frac{1}{\tau}) y^{(3)} + (\omega_h^2 + \frac{2\xi_h \omega_h}{\tau})\ddot{y} + \frac{\omega_h^2}{\tau}\dot{y} \quad (28)$$

Where U represents the input voltage, y denotes the displacement of the piston rod, τ corresponds to the time constant of the hydraulic cylinder, ω_h refers to the natural frequency of the hydraulic cylinder, ξ_h is the hydraulic damping ratio of the cylinder, K_a represents the proportional amplification factor, K_b denotes the flow gain of the electro-hydraulic proportional valve, K_q is the spool valve flow gain coefficient, and A represents the effective working area of the rodless chamber of the hydraulic cylinder. The parameters of the boom and arm hydraulic cylinder control system are listed in Table 1.

Table 1: Hydraulic control system parameter table

Parameters	Boom	Arm
τ	0.0318	0.0318
ω_h	755.497 Hz	843.049 Hz
ξ_h	0.0625	0.0383
A	5.766×10^{-3} m^2	7.821×10^{-3} m^2
k_a	0.3 A/V	0.3 A/V
K_b	6.014×10^{-3} m^3/(s · A)	6.014×10^{-3} m^3/(s · A)
K_q	2.539 m^2/s	2.539 m^2/s

In the case of excavator bucket tine grading operations, for example, the completion of the grading task requires the continuous cooperation of the boom and the arm hydraulic cylinders. An interpolation method [21] is used to plan the trajectory of the tooth tips to obtain the displacement reference values for the boom and arm hydraulic cylinders, as shown in Fig. 2.

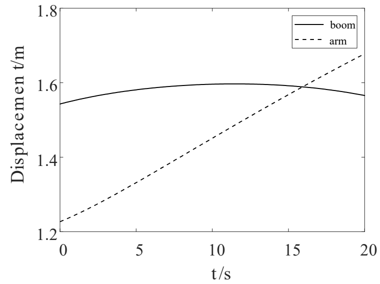

Fig. 2 Boom and arm hydraulic cylinder displacement reference values

In the simulation experiments, the system (28) is discretized into the form of differential equations as shown in Equation (1), and the proposed DD-GPC control algorithm is compared with three other control algorithms: PID, GPC [22], and PFDL-MFAC [23].

In order to ensure the optimal performance of the PID controller, we carried out several simulation tests using the trial-and-error method and finally determined a set of PID controller parameters with relatively ideal performance, i.e., $K_p = 2.8$, $K_i = 0.1$, and $K_d = 0.5$. Since PFDL-MFAC exhibits good robustness, the control algorithm in [24] is used for the simulation experiments. The selected parameters for PFDL-MFAC are $\eta = 0.9$, $\mu = 0.5$, $\rho = 0.9$, $\lambda = 0.2$ and $\varepsilon = 5\times10^{-4}$.

The GPC controller parameters N_P, N_c, λ, η, n_y, and α are chosen to be consistent with the corresponding parameters in DD-GPC. Based on these parameters, the time delay parameter is set to $d = 6$. The parameter settings for DD-GPC are listed in Table 2.

Table 2: DD-GPC parameter

Parameters	Value	Parameters	Value
N_p	18	n_y	4
N_c	18	n_u	10
λ	20	N	20
η	0.001	α	0.12
K_e	1.5		

To evaluate the performance of the four control methods, this study adopts the Root Mean Square Error (RMSE) as the evaluation metric. RMSE is defined as follows:

$$RMSE(\cdot) = \sqrt{\frac{1}{N}\sum_{n=1}^{N} \left\| s_n \right\|^2} \quad (29)$$

Where N is the total number of samples, and s_n represents the deviation distance between the actual position at the nth sampling instant and the corresponding position on the ideal trajectory.

In the initial phase of the simulation, all four controllers were not able to immediately track the displacement of the hydraulic cylinders due to the introduction of additional time delays. However, due to the incorporation of error feedback in the reference value, the proposed DD-GPC control method is significantly more responsive compared to GPC and PID controllers.

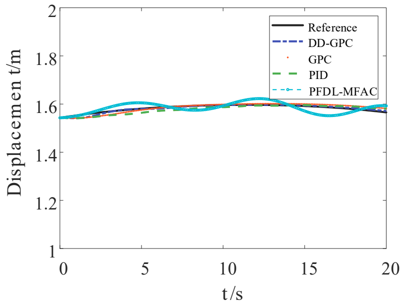

Fig. 3 Boom hydraulic cylinder displacement tracking effect

Once the system enters the stabilization phase, the simulation results in Figs. 3 and 4 show that the proposed method achieves significantly better trajectory tracking performance on both planned trajectories compared to the other three methods. This suggests that the integration of data-driven techniques into GPC can be an effective solution to the problem of time delays and nonlinear characteristics of hydraulic excavators.

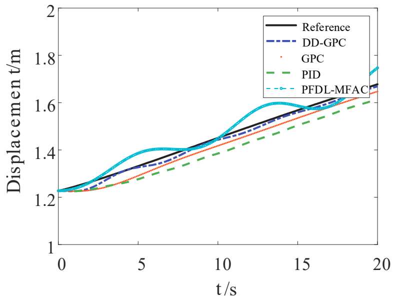

Fig. 4 Arm hydraulic cylinder displacement tracking effect

In contrast, although the PFDL-MFAC responds faster, it exhibits significant oscillations. Given that excavator operations require the coordinated movement of two or three hydraulic arms, this oscillation may adversely affect operational efficiency and quality.

Based on the above analysis, the comparison of bucket tooth tip grading effects in Figure 5 shows that the vertical fluctuation of the proposed method is minimized and the grading operation is accomplished in a higher degree.

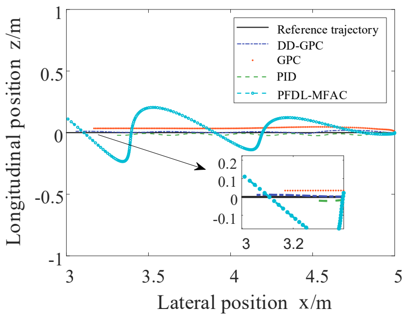

Fig. 5 Block schematic for the DD-GPC

In contrast, in the PFDL-MFAC condition, a coordination problem between the hydraulic arms occurred due to the oscillation of the two arms during tracking, resulting in large fluctuations in the vertical position. Compared to the GPC and PID methods, although the vertical motion is relatively stable, the presence of steady state error and hysteresis effect leads to lower completion accuracy in the horizontal direction and lower steady state error in the vertical direction.

A comparison of the RMSE of the four methods is shown in Table 3. It can be observed that the proposed method achieves the lowest RMSE among all four control strategies.

Table 3: Comparison of the flat-ground performance of the DD-GPC algorithm with other algorithms

Algorithm	RMSE	Improvement (%)
PID	0.2572	——
GPC	0.1763	31.45%
DD-GPC	**0.0718**	**72.083%**
PFDL-MFAC	0.1400	45.567%

In summary, the proposed DD-GPC method provides excellent control performance for nonlinear time-delay systems. In addition, in the compound motion grading operation of the excavator, it is more responsive, and the grading performance is significantly better than the other three methods.

Based on the above simulation results, the proposed control method is well suited for the excavator system and shows excellent control performance in the excavator compound operation. This validates the superiority and effectiveness of the proposed method in dealing with nonlinearities and time delays in excavator systems.

5 Conclusion

This paper proposes an intelligent control approach based on DD-GPC, which is based on a HOFA system model. Firstly, a generalized predictive controller is designed to compensate for the time delay of the system. Then, within the framework of the HOFA system model, online updating of the controller parameters is achieved using data-driven control theory without the need for a global mathematical model. In addition, the response speed of the system is further improved by dynamically adjusting the reference value by introducing an error feedback mechanism in the future reference value. The simulation results of the excavator grading operation validate the effectiveness of the proposed method in solving nonlinearities and time delays. In future work, this approach will be tested on an actual excavator to assess its feasibility in a complex operating environment.

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