High-Clearance Four-Wheel Independent Drive Sprayer Path Tracking Model Predictive Control Postprint

Authors: Wang Zijie, Liu Guohai, Zhang Duo, Shen Yue, Yao Zhen, Zhang He

Date: 2023-02-17T00:00:00+00:00

Abstract

To address issues such as low transmission efficiency, high carbon emissions, environmental pollution, low intelligence level, and poor flexibility in conventional fuel-driven, front-wheel-steered high-clearance sprayers, this study proposes an unmanned high-clearance Four Wheel Independent Drive (4WID) sprayer. The system employs a hybrid powertrain and a 4WID configuration with front and rear dual steering axles, featuring a small turning radius and highly consistent trajectories between front and rear wheels, thereby reducing crop crushing during field plant protection operations. Considering challenges such as drive wheel slip and bogging down in extreme paddy field operating environments, a hierarchical path tracking control framework accounting for drive wheel slip is constructed based on the Linear Time-Varying (LTV) kinematic model of the sprayer. The upper-layer Model Predictive Control (MPC) controller determines the sprayer' s steering angle and motion speed according to the desired path and current vehicle position to achieve path tracking. The lower layer implements a drive wheel slip controller using fuzzy control and integral separation PID control, thereby enabling effective control of path tracking, motion speed, and drive wheel slip, and enhancing the stability and path tracking accuracy of the sprayer in complex operating environments. Co-simulation results using Adams/Matlab demonstrate that under complex operating conditions, the slip rate of the sprayer' s drive wheels remains controlled within $±$20%, preventing excessive wheel slip from adversely affecting vehicle speed and steering angle, which is conducive to improved sprayer stability. The proposed sprayer can rapidly and accurately track the desired path, and compared with control strategies that neglect drive wheel slip, it can adapt to more complex working environments with significant improvements in tracking accuracy.

Full Text

Path Following Model Predictive Control of Four-Wheel Independent Drive High Ground Clearance Sprayer

WANG Zijie, LIU Guohai*, ZHANG Duo, SHEN Yue, YAO Zhen, ZHANG He

(School of Electrical and Information Engineering, Jiangsu University, Zhenjiang, 212013, China)

Abstract: To address the issues of low transmission efficiency, high carbon emissions, environmental pollution, low intelligence, and poor flexibility in traditional fuel-driven, front-wheel steering high ground clearance sprayers, this study proposes a novel high ground clearance four-wheel independent drive (4WID) sprayer suitable for unmanned operation. The sprayer adopts a hybrid power system and a dual steering axle configuration (front and rear), resulting in a small turning radius and highly consistent trajectories between front and rear wheels, which reduces crop damage during field plant protection operations. Considering wheel slip and sinking problems in extreme paddy field operating environments, a hierarchical path following control strategy that accounts for driving wheel slip is constructed based on the linear time-varying (LTV) kinematic model of the sprayer. The upper-layer model predictive control (MPC) obtains the steering angle and motion speed of the sprayer according to the desired path and current vehicle position to achieve path following. The lower layer employs fuzzy control and integral separation PID control to construct a driving wheel slip controller, thereby achieving effective control of path following, motion speed, and driving wheel slip, and improving the stability and path following accuracy of the sprayer in complex operating environments. Co-simulation results using Adams and Matlab demonstrate that under complex working conditions, the slip rate of the sprayer' s driving wheels remains controlled within $±$20%, preventing excessive slip from adversely affecting vehicle speed and steering angle, which enhances sprayer stability. The sprayer can quickly and accurately track the desired path. Compared with control methods that do not consider driving wheel slip, the proposed approach adapts to more complex working environments and shows significant improvement in tracking accuracy.

Keywords: front and rear double steering axles; four-wheel independent drive; model predictive control; fuzzy control; slip; path following

---

1 Introduction

Unmanned agricultural machinery and autonomous operation represent a crucial research direction for future smart agriculture [1]. Agricultural equipment has been designated as one of the ten key research areas in “Made in China 2025” [2]. However, most current agricultural machinery employs fuel drive and traditional mechanical transmission, suffering from low transmission efficiency, single control mode, large turning radius, and difficult attitude control, resulting in relatively backward overall technical levels. Moreover, prolonged operation times, high labor intensity for operators, and safety hazards are common problems [3]. Unmanned agricultural machinery, aided by satellite navigation systems, can better adapt to complex field operating environments, significantly improve operation precision, avoid repetitive or missed operations, and enhance agricultural production efficiency and intelligence levels [4]. Simultaneously, it effectively reduces operator labor intensity and labor costs while avoiding potential human contact with pesticides during plant protection spraying.

Safe driving and path following are core research issues for unmanned agricultural machinery. The performance of control algorithms directly affects navigation accuracy and stable operation of agricultural equipment, consequently impacting operation effectiveness and production efficiency. Complex agricultural operating environments not only reduce path tracking accuracy but also adversely affect safe operation, potentially causing rollover accidents [5]. In recent years, researchers have conducted in-depth studies on path following control [6]. Song et al. [7] considered the influence of longitudinal speed and road curvature on trajectory tracking stability of sprayers under low-speed complex driving conditions, designing a time-varying model predictive control (MPC) to improve trajectory tracking accuracy. Liu et al. [8] proposed a novel dual successive projection-based model-free adaptive control algorithm to solve lateral tracking control problems. Lenain et al. [9] explicitly considered sliding effects through an extended kinematic model, proposing developments in adaptive and predictive observer-based control dedicated to automatic guidance of agricultural tractors. Zhang et al. [10] proposed an improved path following algorithm based on the pure pursuit model, using a particle swarm algorithm to determine the look-ahead distance in real-time to improve straight-line tracking accuracy during agricultural operations. Wang et al. [11] proposed a path following control method for agricultural machinery navigation based on a preview tracking model, effectively improving anti-interference capability on complex road surfaces. Liu et al. [12] proposed a straight-line path following control algorithm for a Leiwo high ground clearance sprayer using position deviation and heading deviation as state variables, enabling automatic straight-line driving, headland turning, and spraying operations. Bai et al. [13] proposed two real-time optimization schemes based on nonlinear model predictive control to ensure control accuracy when tracking reference paths with rapidly changing curvature and heading. Liu et al. [14] proposed a path following control method based on nonlinear model predictive control, effectively reducing lateral deviation.

However, the aforementioned literature does not consider the impact of agricultural machinery slip on stable operation and path following accuracy in complex operating environments. Therefore, overcoming problems such as slipping and sinking of intelligent agricultural machinery in complex and harsh operating environments to achieve stable operation and high-precision tracking is the primary task of agricultural machinery path following control. To address these issues, our research team developed a four-wheel independent drive (4WID) high ground clearance sprayer (Fig. 1 [Figure 1: see original paper]). It adopts a front and rear double steering axle configuration with a 4WID hub motor distributed chassis system (Fig. 2 [Figure 2: see original paper]) [15], featuring strong driving force and small turning radius. Auxiliary steering devices with hydraulic push rods and linkages ensure that front and rear wheels maintain highly consistent trajectories when operating in muddy fields or paddy fields. Taking this 4WID high ground clearance sprayer as the research object, MPC is employed to achieve path following control. Considering the impact of driving wheel slip on path following control when the sprayer operates in muddy fields, a fuzzy controller is added to control the slip rate of driving wheels, thereby improving path following accuracy.

---

2 Sprayer Kinematic Model

Due to the complex operating environment of the sprayer, relying solely on four-wheel differential steering cannot achieve reliable steering or ensure highly consistent front and rear wheel trajectories when passing through muddy paddy fields or potholed roads. Therefore, auxiliary steering devices with linkages and hydraulic push rods are adopted to reduce the influence of road conditions on steering angle even in complex environments.

2.1 Sprayer Differential Steering Kinematic Model

The high ground clearance 4WID sprayer achieves steering through a unique front and rear double steering axle structure combined with coordinated differential hub motors, resulting in a small turning radius and highly consistent front and rear wheel trajectories. The specific parameters of the sprayer are shown in Table 1 .

Table 1 Parameters of 4WID high ground clearance sprayer

Parameter	Value
Mass/kg	
Tire radius/m	
Driving wheel moment of inertia/$(\mathrm{kg \cdot m^2})$	
Linkage length/m	
Boom length/m	
Tank capacity/L	
Spray rate/$(\mathrm{L \cdot min^{-1}})$	
Maximum steering angle/(°)	

Typically, during plant protection operations, the sprayer operates at low speeds. Therefore, this study does not consider sideslip or yaw stability issues, focusing only on path following. According to the chassis drive structure shown in Fig. 2 and based on the Ackermann-Jeantand steering principle [16], the relationship between the sprayer steering angle and four driving wheel speeds is given by formulas (1)-(4).

$$\cos\alpha - \cos\beta - W\tan\alpha \tag{1}$$
$$W\tan\alpha \tag{2}$$
$$W\tan\beta \tag{3}$$
$$W\tan\beta \tag{4}$$

where α and β are the front and rear axle steering angles (°); a is the distance from the front suspension midpoint to the sprayer' s center of mass (m); b is the distance from the rear suspension midpoint to the sprayer' s center of mass (m). The sprayer' s chassis structure is symmetrical, with equal but opposite steering angles for front and rear axles during turning. V is the sprayer' s travel speed (m/s); V_1-V_4 are the speeds of the four driving wheels (m/s). By controlling the speeds of the four driving wheels, vehicle speed and steering motion can be controlled to achieve desired path following.

The relationship between steering angle δ_f and hydraulic push rod length l_t is given by formula (5).

$$\Delta l_t = \begin{cases} -0.00013\delta_f^2 + 0.025\delta_f & \delta_f \leq \\ 0.000096\delta_f^2 + 0.0274\delta_f & \end{cases}$$

2.2 Sprayer Driving Wheel Dynamics Model

To better analyze the state of driving wheels under complex road conditions, a dynamics model of the sprayer driving wheel is established as shown in Fig. 3 [Figure 3: see original paper]. Ignoring air resistance and other disturbances, the dynamics equation for the sprayer driving wheel is given by formula (6).

$$J\dot{\omega} = T_i - RF_l -$$

The driving wheel torque can be expressed as:

$$\dot{\omega} = \frac{T_i - RF_l - T_b}{J}$$

where $\dot{\omega}$ is the driving wheel angular acceleration (rad/s^2); T_i is the driving torque (N·m); R is the driving wheel load radius (m); T_b is the rolling resistance torque (N·m); F_l is the tire longitudinal force (N); J is the driving wheel moment of inertia (kg/m^2). As shown in formula (8), M is the mass of the sprayer driving wheel.

2.3 Sprayer Linear Time-Varying Kinematic Model

The longitudinal velocity at the sprayer's center point is selected as the machine' s longitudinal speed. The state variables are selected as the X-axis position, Y-axis position, and heading angle ϕ in the global coordinate system; the control variables are the sprayer' s longitudinal speed v_r and steering angle δ_f. The sprayer length is l. Based on kinematic principles, the relationship between the sprayer' s overall speed, steering angle, and position in the global coordinate system is given by formula (9).

$$\dot{X} = v_r \cos\phi \tag{5}$$

$$\dot{Y} = v_r \sin\phi \tag{6}$$

$$\dot{\phi} = \frac{2v_r \tan\delta_f}{l} \tag{7}$$

By controlling the four driving wheel speeds, vehicle speed and steering motion can be controlled to achieve desired path following.

---

3 LTV-MPC Path Following Control

A hierarchical control structure as shown in Fig. 4 [Figure 4: see original paper] is adopted to control the sprayer' s path following. The upper controller uses linear time-varying model predictive control (LTV-MPC) to achieve path tracking, while the lower controller considers the impact of driving wheel slip on tracking accuracy and employs fuzzy control to regulate driving wheel slip rate, using integral separation PID control to reduce large slip rates during startup.

3.1 Path Following MPC

MPC has the capability to systematically consider predictive information and handle multi-constraint optimization problems, making it widely used in unmanned vehicle path following control [17,18]. The MPC algorithm features a "feedforward + feedback" control structure, using the reference input sequence as feedforward for future inputs and system state values as feedback compensation. Through online solving, it predicts potential constraint violations and takes appropriate control actions in advance. By rolling optimization, it solves relatively simple open-loop optimization problems within a finite time horizon to obtain closed-loop control [19].

To simplify the model, the model is linearized by selecting a reference state x_{ref} and using Taylor expansion at x_{ref}. Formula (10) is rewritten in incremental form to obtain the state space equation for the state error $\tilde{x}$ as shown in formula (11).

$$\dot{\tilde{x}} = f(x_{ref}, u_{ref}) + \frac{\partial f}{\partial x}\tilde{x} + \frac{\partial f}{\partial u}\tilde{u} = A\tilde{x} + B\tilde{u}$$

where A and B are the Jacobians of f with respect to x and u, respectively.

Through forward Euler discretization of formula (11), the sprayer kinematic model can be approximated as a linear time-varying (LTV) system as shown in formula (12).

$$\tilde{x}(k+1) = A_k\tilde{x}(k) + B_k\tilde{u}(k)$$

where $A_{k,t}$ and $B_{k,t}$ are defined as:

$$A_{k,t} = \begin{bmatrix} Tv_r \sin\phi & T\cos\phi & 0 \\ Tv_r \cos\phi & T\sin\phi & 0 \\ \frac{2T\tan\delta_f}{l} & 0 & \frac{2Tv_r}{l\cos^2\delta_f} \end{bmatrix}, \quad B_{k,t} = \begin{bmatrix} T\cos\phi & 0 \\ T\sin\phi & 0 \\ 0 & \frac{2Tv_r}{l\cos^2\delta_f} \end{bmatrix}$$

To prevent abrupt changes in control variables that affect path following accuracy and stability, control increments are used instead of control variables. The modified state equation is expressed as:

$$\zeta(k|t) = \begin{bmatrix} \tilde{x}(k|t) \\ \tilde{u}(k-1|t) \end{bmatrix}$$

where $k|t$ denotes prediction of time k at time t.

The system state is set as shown in formula (15).

$$\eta(k) = \hat{c}_{k,t}\zeta(k|t)$$

where $\eta = [X, Y, \phi]^T$ is the discrete system output. X is the sprayer' s X-axis position (m); Y is the Y-axis position (m); ϕ is the sprayer' s heading angle (°).

The state space equation for MPC can be obtained as:

$$\begin{cases} \zeta(k+1) = \hat{A}\zeta(k) + \hat{B}\Delta u(k) \\ \eta(k) = \hat{c}_{k,t}\zeta(k|t) \\ \Delta u(k) = \tilde{u}(k) - \tilde{u}(k-1) \end{cases}$$

where

$$\hat{A} = \begin{bmatrix} A_{k,t} & B_{k,t} \\ 0_{m\times n} & I_m \end{bmatrix}, \quad \hat{B} = \begin{bmatrix} B_{k,t} \\ I_m \end{bmatrix}, \quad \hat{c}_{k,t} = \begin{bmatrix} c_{k,t} & 0 \end{bmatrix}$$

with m=2 being the control variable dimension and n=3 being the state variable dimension.

Considering that actual sprayers use hydraulic push rods for steering with relatively large response times, and that low-speed pesticide spraying operations do not require high dynamic performance but demand high path following accuracy, large overshoot in MPC output steering angle would inevitably affect tracking accuracy. Therefore, in MPC design, constraints on control variables and increments are applied to match the actual steering system and avoid large overshoot, thereby improving path following accuracy.

To prevent infeasible solutions [20], a slack factor is introduced. The objective function is set as formula (21) [21]:

$$J = \sum_{i=1}^{N_p} (\eta_{ref} - \eta)^T Q (\eta_{ref} - \eta) + \sum_{i=1}^{N_c} \Delta u^T R \Delta u + \rho \varepsilon^2$$

where N_p is the prediction horizon; N_c is the control horizon; Q is the state weight matrix; R is the control weight matrix; ΔU is the control increment matrix; is the system output.

The objective function constraints are set as follows:

$$\begin{cases} \zeta(k+1|t) = \hat{A}\zeta(k|t) + \hat{B}\Delta u \\ \eta(k|t) = c_{k,t}\zeta(k|t) \\ u_{min} \leq u(t+k) \leq u_{max} \\ \Delta u_{min} \leq \Delta u(t+k) \leq \Delta u_{max} \\ \Delta u(t+k) = 0, \quad k = N_c, \ldots, N_p - 1 \\ \varepsilon > 0 \end{cases}$$

3.2 LTV-MPC Controller Design

Through iterative prediction equations, the system predictive output is set as shown in formulas (23)-(26):

$$Y = \Psi_t \zeta(t|t) + \Theta_t \Delta U \tag{8}$$

$$\Psi_t = \begin{bmatrix} \hat{c}_{t,t}\hat{A} \\ \hat{c}_{t,t}\hat{A}^2 \\ \vdots \\ \hat{c}_{t,t}\hat{A}^{N_p} \end{bmatrix}, \quad \Theta_t = \begin{bmatrix} \hat{c}_{t,t}\hat{B} & 0 & \cdots & 0 \\ \hat{c}_{t,t}\hat{A}\hat{B} & \hat{c}_{t,t}\hat{B} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ \hat{c}_{t,t}\hat{A}^{N_p-1}\hat{B} & \hat{c}_{t,t}\hat{A}^{N_p-2}\hat{B} & \cdots & \hat{c}_{t,t}\hat{A}^{N_p-N_c}\hat{B} \end{bmatrix} \tag{9}$$

where N_p is the prediction horizon; ΔU is the control increment matrix; Y is the system output matrix; Ψ_t and Θ_t are equation iteration matrices.

For convenient quadratic programming solution in MATLAB, formula (21) is transformed into the standard form shown in formula (27):

$$\min_{\Delta U,\varepsilon} \frac{1}{2}\Delta U^T H \Delta U + f^T \Delta U + \rho\varepsilon^2$$

where $H = 2\Theta_t^T Q \Theta_t + R$ and $f = 2E^T Q \Theta_t$, with $E = \Psi_t \zeta(t|t)$. Since U cannot control E, the term E^{TQE} is ignored in quadratic programming. To simplify calculation, the first control variable in the control sequence is output to the controlled system as the actual control variable. At the next sampling time (T+1), the above steps are repeated to achieve rolling optimization.

3.3 Driving Wheel Slip Rate Fuzzy Control

Driving wheels of the sprayer generate significant slip during steering and complex operating environments [21,22], which adversely affects stable operation and path following accuracy. Therefore, the impact of driving wheel slip on path following accuracy must be considered [23].

3.3.1 Driving Wheel Slip Rate Analysis A tire characteristic test platform was built in Adams/Car to measure the relationship between tire slip rate and longitudinal force. The longitudinal slip stiffness was set as C_l=10,000 and lateral slip stiffness as C_α=8,000. The relationship between driving wheel longitudinal force and slip rate was determined using the Tire Testrig module in Adams/Car, as shown in Fig. 5 [Figure 5: see original paper].

From Fig. 5, when the driving wheel slip rate is within $±$20%, the tire longitudinal driving force and slip rate have an approximately linear relationship, which can be expressed as formula (29):

$$F_l = C_l s$$

where F_l is the driving wheel longitudinal force (N); s is the slip rate (%), defined as:

$$s = \frac{\max(R\omega, v) - \min(R\omega, v)}{\max(R\omega, v)}$$

where R, ω, and v have the same meanings as in formula (6).

Substituting formulas (29) and (30) into formula (7) yields formula (31), where the parameters have the same meanings as in formula (7).

In complex field operating environments, the driving torque output from the hub motor should be controlled to maintain the driving wheel slip rate within $±$20%. This allows the sprayer to fully utilize road adhesion conditions to obtain large longitudinal driving force while effectively avoiding the "digging" phenomenon caused by wheel spin, which increases the risk of sinking or rollover.

3.3.2 Fuzzy Controller Design In the fuzzy controller, the speed deviation e of the sprayer is used as the input, and the output variable u serves as the desired slip rate s for the tires. After fuzzy quantization processing, the relationship between fuzzy linguistic variables and domain is established according to membership functions. The domain and seven quantization levels of membership functions for e and u are shown in Fig. 6 [Figure 6: see original paper]. The control rules follow the "if A, then B" form, using the Mamdani method to establish the fuzzy rule base (Table 2). The MIN-MAX-gravity method is used for defuzzification to convert to precise output values.

Table 2 Fuzzy control rules

e u	NB	NS	ZO	PS	PB
NB	PB	PS	ZO	NS	NB
NS	PS	PS	ZO	NS	NS
ZO	ZO	ZO	ZO	ZO	ZO
PS	NS	NS	ZO	PS	PS
PB	NB	NS	ZO	PS	PB

---

4 Simulation Results and Analysis

Using MATLAB/Simulink, an LTV-MPC controller and slip fuzzy controller were built and co-simulated with a sprayer model constructed in Adams View. The MPC parameters are set as shown in Table 3 , and the integral separation PID controller parameters are shown in Table 4 .

Table 3 Model predictive controller parameters

Parameter	Value
Sampling time/s	
Control horizon N_c	
Prediction horizon N_p	
Weight matrix Q	200×I_m
Weight matrix R	30×I_n
Wheel angle upper limit/rad	
Wheel angle lower limit/rad	
Wheel angle increment upper limit/rad	
Wheel angle increment lower limit/rad	

Table 4 Integral separation PID controller parameters

Parameter	Value
Sampling time/s	
Proportional control k_p	
Integral control k_i	
Derivative control k_d	

This study analyzed two working conditions: a U-shaped path on a split-friction road surface and a figure-8 path on a 3D random road surface.

4.1 Case 1: U-Shaped Path Following on Split-Friction Road Surface

A split-friction road surface was set with adhesion coefficients of 0.3 and 0.7 for the left and right driving wheels, respectively [24]. The reference path was a continuous U-turn with a radius of 10 m.

Fig. 7 [Figure 7: see original paper] shows the driving wheel slip rates of the sprayer on the split-friction road surface. With only LTV-MPC, when road adhesion coefficients differ, the driving wheels experience inconsistent forces, causing significant slip with maximum slip rates reaching 50%. With the addition of the slip fuzzy controller, slip rates can be controlled within \$±\$20% during startup and steering.

Fig. 8 [Figure 8: see original paper] shows the front wheel steering angle of the sprayer on the split-friction road surface. With only LTV-MPC, driving wheel slip causes large overshoot in steering angle during startup and steering, adversely affecting stability and tracking accuracy. With the slip fuzzy controller, steering angle overshoot is reduced, with actual steering angles of \$±\$4.866°.

The lateral deviation and actual path tracking of the sprayer on the split-friction road surface are shown in Fig. 9 [Figure 9: see original paper] and Fig. 10 [Figure 10: see original paper]. Driving wheel slip affects lateral deviation during path tracking. With only LTV-MPC, slip-induced steering angle overshoot impacts path tracking accuracy, with maximum lateral deviation of 0.032 m. With the slip fuzzy controller, steering angle overshoot is reduced, decreasing maximum lateral deviation to 0.018 m and improving path tracking accuracy in complex operating environments.

4.2 Case 2: Figure-8 Path Following on 3D Random Road Surface

To further test the effectiveness of the path following control under real complex road conditions, a C-level random road surface model was generated in MATLAB based on road roughness classification standards [25] and Adams 3D road node algorithms [26], as shown in Fig. 11 [Figure 11: see original paper]. Co-simulation of figure-8 path following was conducted on the 3D road surface.

Fig. 12 [Figure 12: see original paper] shows the driving wheel slip rates on the C-level random road surface. Due to uneven road surface reducing contact area between driving wheels and ground, driving wheels are more prone to excessive slip, reducing stability and tracking performance. During startup, slip rates of approximately $±$20% occur. During straight-line tracking, slip rates fluctuate due to changing road roughness but remain within $±$20%. During steering, slip rates fluctuate significantly due to roll effects but are basically maintained within $±$20%.

The speed and steering angle waveforms on the C-level random road surface are shown in Fig. 13 [Figure 13: see original paper] and Fig. 14 [Figure 14: see original paper]. Driving wheel slip affects vehicle speed and steering angle. Due to road unevenness, speed and steering angle fluctuate during path tracking, but the control algorithm can promptly adjust driving wheel torque and steering angle to control vehicle attitude and prevent deviation from the reference path. Steering angle fluctuates significantly, with maximum steering angle of 7.71°.

The lateral deviation on the C-level random road surface is shown in Fig. 15 [Figure 15: see original paper]. Large slip rates during startup cause fluctuations in speed and steering angle, resulting in lateral deviation fluctuations during straight-line tracking with maximum deviation of 0.0057 m. During steering, roll effects from road unevenness cause continuous steering angle fluctuations, leading to larger lateral deviation with maximum value of 0.058 m. The tracking results on the C-level random road surface are shown in Fig. 16 [Figure 16: see original paper]. The sprayer can accurately track the desired path under complex conditions. By controlling driving wheel slip rates and preventing wheel spin, stability and control accuracy are improved. The results demonstrate that the control algorithm meets the requirements of complex operating conditions.

5 Conclusion

This study analyzed and established an LTV kinematic model based on MPC for the unique front and rear double steering axle structure synchronized with 4WID of the high ground clearance sprayer. Considering that excessive driving wheel slip reduces sprayer stability and path tracking accuracy, a hierarchical path following control strategy for the 4WID sprayer was constructed using MPC and fuzzy slip control to improve path tracking accuracy in muddy, slippery, and other complex farmland operating environments.

Adams/Matlab co-simulation results show that the proposed controller based on LTV-MPC and slip fuzzy control achieves better stability and tracking accuracy than LTV-MPC alone under complex operating conditions. It reduces steering angle overshoot, quickly and accurately controls vehicle speed and steering angle, and maintains driving wheel slip rates within $±$20%. On split-friction road surfaces with adhesion coefficients of 0.3 and 0.7, lateral deviation can be controlled within $±$0.018 m. On C-level roughness 3D road surfaces, the sprayer can promptly adjust front wheel steering angle to stabilize body attitude, with lateral deviation controlled within $±$0.054 m. The control algorithm effectively reduces lateral deviation and improves path tracking accuracy in complex operating environments.

Future work will involve experimental verification of the proposed path model predictive control using an A&D control instrument (A&D5436) test platform. Additionally, the impact of roll on sprayer stability and control accuracy due to vertical load changes will be further investigated, with comprehensive equivalent constraints for roll added to the model.

References

[1] VOUGIOUKAS S, ARVANITIS K, SIGRIMIS N. A nonlinear model predictive tracking controller for agricultural vehicles[C]// 2007 European Control Conference (ECC). Piscataway, New York, USA: IEEE, 2007: 349-356.

[2] LI J. Thoughts on promoting made in China 2025 with agricultural mechanization transformation and upgrade[J]. Times Agricultural Machinery, 2019, 46(6): 10-11.

[3] HUANG T, JIANG P, HU W, et al. Design and experiment of path tracking system of field management machine[J]. Journal of Zhejiang University, 2020, 46(4): 509-518.

[4] ZHENG W, HUANG S, LIU B. Analysis on development and application of Beidou positioning system in agricultural engineering[J]. Agricultural Equipment & Vehicle Engineering, 2020, 58(7): 143-144.

[5] ZHANG Y. Research on autonomous driving and operation system of unmanned agricultural machines in paddy field environment[D]. Shanghai: Shanghai Jiao Tong University, 2019.

[6] XIONG L, YANG X, ZHUO G, et al. Review on the development of motion control of unmanned vehicle[J]. Journal of Mechanical Engineering, 2020, 56(10): 127-143.

[7] SONG X, SHAO Y, QU Z. A vehicle trajectory tracking method with a time-varying model based on the model predictive control[J]. IEEE Access, 2020, 8: 3842-3850.

[8] LIU S, HOU Z, TIAN T, et al. A novel dual successive projection-based model-free adaptive control method and application to an autonomous car[J]. IEEE Transactions on Neural Networks and Learning Systems, 2019, 30(11): 3444-3457.

[9] LENAIN R, THUILOT B, CARIOU C, et al. Mobile robot control in presence of sliding: Application to agricultural vehicle path tracking[C]// The 45th IEEE Conference on Decision and Control, San Diego, CA. Piscataway, New York, USA: IEEE, 2006: 6004-6009.

[10] ZHANG H, WANG G, LYU Y, et al. Research on path tracking algorithm of agricultural machinery based on improved pure tracking model[J]. Transactions of the CSAM, 2020, 51(9): 18-25.

[11] WANG H, WANG G, LUO X, et al. Tracking control method of agricultural machinery navigation path based on preview tracking model[J]. Transactions of the CSAE, 2019, 35(4): 11-19.

[12] LIU Z, ZHANG Z, LUO X, et al. Design of GNSS automatic navigation operation system for Leiwo ZP9500 high ground clearance sprayer[J]. Transactions of the CSAE, 2018, 34(1): 15-21.

[13] BAI G, LIU L, MENG Y, et al. Real-time path tracking of mobile robot based on nonlinear model predictive control[J]. Transactions of the CSAM, 2020, 51(9): 47-52, 60.

[14] LIU Z, ZHANG W, LYU Z, et al. Design and test of path tracking controller for agricultural vehicle based on nonlinear model[J]. Transactions of the CSAM, 2018, 49(7): 23-30.

[15] SHEN Y, HE S, LIU H, et al. Design and test of self-steering electric chassis control system for highland gap sprayer[J]. Transactions of the CSAM, 2020, 51(11): 385-392, 402.

[16] QIU H. Research on four wheel drive differential steering control system based on hub motor[D]. Chongqing: Southeast University, 2012.

[17] YOON S, JEON H, KUM D. Predictive cruise control using radial basis function network-based vehicle motion prediction and chance constrained model predictive control[J]. IEEE Transactions on Intelligent Transportation Systems, 2019, 20(10): 3832-3843.

[18] TANG Z, XU X, WANG F, et al. Coordinated control for path following of two-wheel independently actuated autonomous ground vehicle[J]. IET Intelligent Transport Systems, 2019, 13(4): 628-635.

[19] LIU Y, YU S, GUO Y, et al. Model predictive control based on extended state observer for vehicle yaw stability[J]. Control Theory & Applications, 2017, 34(4): 424-432.

[20] LIU H, LI T, NIE Y, et al. Research on torque allocation strategy based on predicted sliding ratio[J]. Automotive Technology, 2020, 540(9): 39-44.

[21] LI S, WANG J, LI K. Stability method of soft-constrained linear model predictive control system[J]. Journal of Tsinghua University (Natural Science Edition), 2010, 50(11): 1848-1852.

[22] LIU Y, GU R, WANG Y. Development trend and industrialization prospect analysis of self-propelled boom sprayer with high ground clearance[J]. Times Agricultural Machinery, 2018, 45(9): 36-37.

[23] MAO J, ZHOU J, LIANG Y. Research on sliding mode control of slip ratio of electrically driven vehicles with high ground gap[J]. Journal of China Agricultural University, 2017, 22(2): 129-134.

[24] ZHANG W, XU L. Automobile Theory (3rd edition)[M]. Beijing: Machinery Industry Press, 2018.

[25] SHEN J, SONG J. Research on ABS braking on random uneven roads[J]. Automotive Engineering, 2007(3): 230-233, 237.

[26] WANG Q. Research on dynamic modeling and simulation of driving stability of high ground clearance sprayer[D]. Shihezi: Shihezi University, 2020.

Note: Figure translations are in progress. See original paper for figures.