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Original Paper

Simulation Research on Adaptive Control System of Combine Harvester Feeding Rate Based on Fuzzy PID

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Abstract

During field operations, combine harvesters frequently encounter significant fluctuations in feeding rates attributable to the stochastic nature of crop density and uneven growth patterns. These irregularities often precipitate critical mechanical failures, such as threshing drum blockages and engine stalling. To mitigate these operational risks, this study proposes a robust adaptive control strategy for feeding rate regulation rooted in fuzzy logic. Initially, a mathematical model of the system dynamics is constructed by analyzing the nonlinear coupling between the harvester's forward speed and the feeding rate, incorporating characteristics of significant inertia and pure time delay. Addressing the inherent limitations of conventional PID algorithms—specifically their inadequate parameter adaptability and weak disturbance rejection under complex, time-varying conditions—a fuzzy adaptive PID controller is designed. This controller utilizes the feeding rate error (E) and its rate of change (EC) as inputs to facilitate online, real-time tuning of the proportional (K_p), integral (K_i), and derivative (K_d) parameters via a fuzzy inference mechanism. Simulation experiments conducted on the MATLAB/Simulink platform demonstrate that, compared to traditional PID control, the proposed system reduces overshoot by approximately 14.2% (from 18.3% to 4.1%) when subjected to step changes in crop density. Furthermore, the settling time is significantly truncated, and steady-state error is effectively eliminated. These results corroborate that the proposed control strategy exhibits superior robustness and dynamic tracking capabilities, thereby satisfying the rigorous requirements for automated operation in modern precision agriculture.

Keywords

combine harvester, Fuzzy PID, adaptive control, HST, Matlab/Simulink

1. Introduction

As the cornerstone of modern agricultural production systems, the combine harvester's operational efficiency and quality are determinants of both grain harvesting success and production cost control. However, in practical field harvesting scenarios, the operational environment is characterized by high uncertainty and time-variance, influenced by uncontrollable factors such as crop planting density, variability in plant height, soil moisture content, and lodging conditions. These environmental disparities directly result in severe fluctuations in the machine's instantaneous feeding rate, which acts as a critical bottleneck restricting performance enhancement.

The feeding rate serves as a pivotal technical indicator for characterizing the load status of a combine harvester. A sustained feeding rate exceeding the rated threshold not only overloads the threshing drum, inducing blockages, but in severe cases can also cause engine stalling or fatigue damage to key mechanical components. Conversely, prolonged operation at a low feeding rate fails to utilize the capacity of high-power models, leading to operational inefficiencies and fuel wastage. Consequently, maintaining the feeding rate in a dynamic equilibrium near the rated value by real-time adjustment of the travel speed is the core approach to achieving "high quality, high efficiency, and low loss" in harvesting operations.

Traditional combine harvester operations predominantly rely on the driver manually adjusting the handle of the Hydrostatic Transmission (HST) based on engine sound or personal experience to control vehicle speed. This "open-loop" operational mode is labor-intensive and, limited by the driver's physiological reaction lag and subjective judgment errors, struggles to adapt to complex and variable farmland conditions. With the acceleration of mechatronics in agricultural equipment, feeding rate adaptive systems based on automatic control theory have emerged as a research hotspot globally.

Internationally, the automation of agricultural machinery in developed countries began early. Agricultural giants such as John Deere and CLAAS initiated relevant exploration as early as the 1980s. The technological evolution has progressed from early simple mechanical-hydraulic feedback to multi-sensor fusion control based on drum torque and header auger torque in the 1990s. In recent years, high-end foreign models have begun to incorporate modern control theories and artificial intelligence. For instance, the CEMOS AUTOMATIC system introduced by CLAAS innovatively combines machine vision with Model Predictive Control (MPC), enabling crop flow prediction and automatic optimization of whole-machine parameters.

Domestic research in this field started relatively late but has shown rapid catch-up momentum. Universities such as Jiangsu University, China Agricultural University, and Jilin University have accumulated significant findings in feeding rate detection mechanisms and control algorithms. Current research primarily focuses on two dimensions: first, high-precision sensing technologies, covering torque sensing, hydraulic pressure monitoring, and machine vision solutions; second, the optimization of control algorithm robustness. Although conventional PID control has been applied in some domestic models, the crop-machine interaction system exhibits typical characteristics of nonlinearity, large time delays, and time-varying parameters. Traditional PID controllers with fixed parameters struggle to balance response speed and stability, often resulting in significant overshoot oscillations or response lag when encountering sudden changes in crop density.

Addressing these engineering challenges, this paper focuses on the feeding rate control system of combine harvesters, specifically exploring a parameter-adaptive PID control strategy based on fuzzy logic. By establishing a system dynamic mathematical model, designing fuzzy inference rules, and conducting multi-scenario simulation comparative analysis using Matlab/Simulink tools, this study aims to identify a control solution with rapid response, minimal overshoot, and strong interference rejection capabilities, providing a theoretical basis and technical support for the intelligent upgrading of domestic high-end combine harvesters.

2. Materials and Methods

2.1 Mathematical Model of Feeding Rate and Travel Speed

The core of stable feeding rate control for combine harvesters lies in automatically regulating the machine's travel speed in response to inconsistent crop growth density, thereby maintaining the material entering the header per unit time within a set range. Typically, this involves using key component load sensors, vision systems, or LiDAR to detect the feeding rate. A controller receives the error signal, computes the control variable, and acts on the harvester's Hydrostatic Transmission (HST) system, adjusting the swashplate angle of the hydraulic pump to alter the hydraulic motor speed, thus controlling the harvester's travel speed (Figure 1).

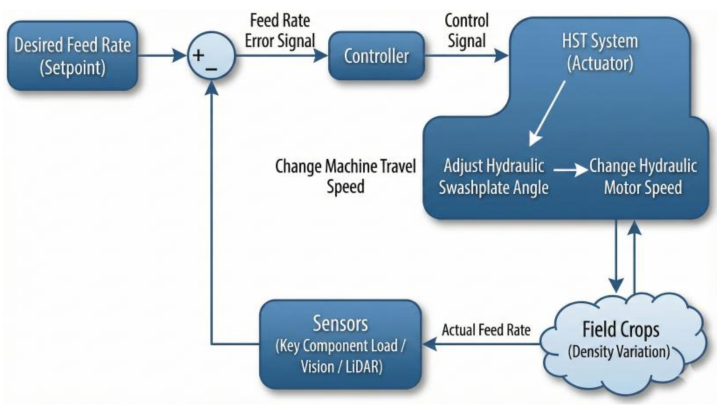

Figure 1. Schematic Diagram of the Feeding Rate Control System

Assuming the combine harvester travels in a straight line on a flat field with a constant header height, the feeding rate Q (kg/s) can be expressed as the product of crop attributes and machine parameters:

$Q(t)=\rho\cdot h\cdot w\cdot v(t)$

Where:

ρ: Crop density (kg/m^3)

h: Crop height(m)

w: Cutting width (m)

$v(t)$: Forward speed of the harvester (m/s)

During field operation, sensors detect the current feeding rate signal $y(t)$ in real-time and feed it back to the controller for comparison with the set value $r(t)$.

If $y(t)<r(t)$ (insufficient feeding), the controller issues a command to increase the HST pump displacement, accelerating the machine.

If $y(t)>r(t)$ (excessive feeding), the controller issues a command to decrease the HST pump displacement, decelerating the machine.

Letting $K_{crop}=\rho\cdot h\cdot w$ be the crop coefficient, and assuming crop density and height are relatively uniform over a short period, the feeding rate $Q(t)$ is directly proportional to the forward speed $v(t)$. This constitutes the basis of control: by regulating $v(t)$, $Q(t)$ can be linearly altered.

2.2 Dynamic Mathematical Model of the Control Object

In practical control scenarios, the system is not instantaneous but exhibits inertia and lag. It is necessary to establish the dynamic transfer function for the "travel speed input $\to$ feeding rate output". The HST system controls the pump displacement via an electro-hydraulic proportional valve. Considering the control current (or voltage) as the input and machine speed as the output, and given that the hydraulic system's response speed significantly exceeds the mechanical system's inertia, it can typically be simplified as a proportional element:

$$G_{HST}(s)\approx K_{HST}$$

Or, for greater precision, it is modeled as a first-order inertial element with a small time constant:

$$G_{HST}(s)=\frac{K_{HST}}{T_{HST}s+1}$$

Where K_{HST} is the flow gain of the hydraulic system, and T_{HST} is the hydraulic response time constant (typically very small, approximately 0.1s to 0.2s, often negligible in system simulations).

The modeling of the feeding process is critical. When a speed command is issued, changes in the feeding rate are primarily influenced by two factors:

Pure Delay: The time required from the cutter severing the crop to the crop passing through the reel, retractable fingers, and auger, finally entering the feeder house and reaching the threshing drum (sensor location). This duration is the pure delay time τ.

$$\tau=\frac{L}{v_c}$$

Where $L$is the physical distance from the cutter to the sensor, and v_c is the crop transport speed within the machine. Typically, $\tau\approx 1.0s$.

System Inertia (T_{sys})**:** The combine harvester possesses a large overall mass, meaning speed changes require time (mechanical inertia). Simultaneously, the establishment of crop flow within the drum is also a gradual process. This manifests as first-order inertial characteristics.

Consequently, the “speed-feeding rate” system of the combine harvester is generally modeled as a standard first-order inertial element with pure delay:

$G_p(s)=\frac{K}{Ts+1}e^{-\tau s}$

Where: K is the process gain (reflecting the magnitude of feeding rate change per unit speed change); T is the system time constant (reflecting acceleration speed, typically 2.0s ~ 4.0s); and τ is the pure delay time (typically ~1.0s).

Assuming a torque sensor is used to detect the drum shaft torque to characterize the feeding rate, the sensor’s dynamic response is usually rapid and can be approximated as a proportional element (K_{sensor}). To filter out high-frequency noise from engine vibration and field unevenness, a low-pass filter is typically connected in series in practical engineering:

$G_f(s)=\frac{1}{T_f s+1}$

Where T_f is the filter time constant.

Combining these elements and neglecting minor factors, the open-loop transfer function of the entire combine harvester feeding rate control system can be simplified as:

$$G(s)=\frac{K_{total}}{T_\Sigma s+1}e^{-\tau s}$$

Where K_{total} is the total system gain, T_Σ is the dominant system time constant, an dτ is the total system delay time.

3. Research Design

3.1 Model Construction

Given the nonlinearity, time-variance, and significant lag inherent in the “travel speed-feeding rate” mathematical model of the combine harvester, a single conventional PID controller struggles to maintain optimal control performance across all operating conditions. Therefore, this chapter proposes a parameter self-tuning fuzzy PID control strategy. This strategy retains the simple structure and high steady-state accuracy of conventional PID control while utilizing fuzzy inference to monitor the system state in real-time and adjust the three PID control parameters(K_p,K_i,K_d) online. The system structure comprises two main components:

1. Conventional PID Control Loop: Directly operates on the error to output the control variable.
2. Fuzzy Inference Mechanism: Based on the error (e) and the rate of change of error(ec), it calculates the correction values (ΔK_p,ΔK_i,ΔK_d)for the PID parameters via fuzzy rules.

3.2 Conventional PID Control Principle

PID control is the most established algorithm in industrial applications. In the continuous time domain, its control law is defined as:

$u(t)=K_p e(t)+K_i\int_0^t e(\tau)d\tau+K_d\frac{de(t)}{dt}$

Or in the common engineering form:

$$G_c(s)=K_p+\frac{K_i}{s}+K_d s$$

Where:

K_p (Proportional Coefficient): Determines the system's response speed. A larger K_p yields a faster response but excessive values can cause overshoot or oscillation.

K_i (Integral Coefficient): Used to eliminate steady-state error. Larger values eliminate static error faster but may induce integral saturation.

K_d (Derivative Coefficient): Reflects the trend of error change, providing predictive capability to suppress overshoot and improve dynamic characteristics.

In combine harvester operations, due to drastic changes in crop density, a fixed set of K_p,K_i,K_d often involves trade-offs. For instance, a larger$K_p$is required to respond quickly to sudden density changes, but this leads to frequent speed oscillations when density is uniform. Hence, fuzzy control must be introduced for dynamic parameter adjustment.

3.3 Fuzzy Controller Design

This study adopts a Mamdani-type fuzzy controller with two inputs and three outputs.

Input Variables: Feeding rate error $e(t)$ (difference between set value $r(t)$ and actual value$y(t)$) and error change rate $ec(t)(de(t)/dt)$.

Output Variables: PID parameter corrections $\Delta K_p,\Delta K_i,\Delta K_d$.

To facilitate fuzzy inference, the physical domain is mapped to a standard Universe of Discourse. The fuzzy universe for all input and output variables is set as an integer domain: $\{-3,-2,-1,0,1,2,3\}$. Quantization factors are defined to convert physical values to fuzzy values (referencing Simulink design): Error quantization factor K_e and Error change rate quantization factor K_{ec}.

The universe is discretized into 7 linguistic levels: NB (Negative Big), NM (Negative Medium), NS (Negative Small), ZO (Zero), PS (Positive Small), PM (Positive Medium), PB (Positive Big).

Membership Functions: The triangular membership function (Trimf) is selected for E,EC, and output variables due to its high sensitivity in capturing minute changes.

Fuzzy Rules: The rule base is the core "knowledge repository" of the controller. Based on the influence of PID parameters on system performance and expert operational experience, the following tuning principles are formulated:

1. When error $|e|$ is large (e.g., encountering lodging or open patches): A larger K_p is taken to accelerate response. K_i is set to zero or a minimal value (integral separation) to prevent saturation-induced overshoot. K_d is kept small to avoid noise sensitivity.

2. When error$|e|$ is medium: K_p takes a smaller value for smooth transition; $K_i$increases moderately to reduce static error; K_d takes a medium value to ensure damping.

3. When error $|e|$ is small (near steady state): Both K_p and $K_i$should increase to eliminate static error and improve precision. K_d selection depends on the sign of ec; if approaching the setpoint positively, K_d increases for braking.

Table 3-1. Fuzzy Control Rule Table for ΔK_p

E \ EC	NB	NM	NS	ZO	PS	PM	PB
NB	PB	PB	PM	PM	PS	ZO	ZO
NM	PB	PB	PM	PS	PS	ZO	NS
NS	PM	PM	PM	PS	ZO	NS	NS
ZO	PM	PM	PS	ZO	NS	NM	NM
PS	PS	PS	ZO	NS	NS	NM	NM
PM	PS	ZO	NS	NM	NM	NM	NB
PB	ZO	ZO	NM	NM	NM	NB	NB

Table 3-2. Fuzzy Control Rule Table for ΔK_i

E \ EC	NB	NM	NS	ZO	PS	PM	PB
NB	NB	NB	NM	NM	NS	ZO	ZO
NM	NB	NB	NM	NS	NS	ZO	ZO
NS	NB	NM	NS	NS	ZO	PS	PS
ZO	NM	NM	NS	ZO	PS	PM	PM
PS	NM	NS	ZO	PS	PS	PM	PB
PM	ZO	ZO	PS	PS	PM	PB	PB
PB	ZO	ZO	PS	PM	PM	PB	PB

Table 3-3. Fuzzy Control Rule Table for ΔK_d

E \ EC	NB	NM	NS	ZO	PS	PM	PB
NB	PS	NS	NB	NB	NM	NS	PS
NM	PS	NS	NB	NM	NS	NS	ZO
NS	ZO	NS	NM	NM	NS	NS	ZO
ZO	ZO	NS	NS	ZO	ZO	ZO	ZO

PS	ZO	ZO	ZO	ZO	ZO	ZO	ZO
PM	PB	NS	PS	PS	PS	PS	PB
PB	PB	PM	PM	PM	PS	PS	PB

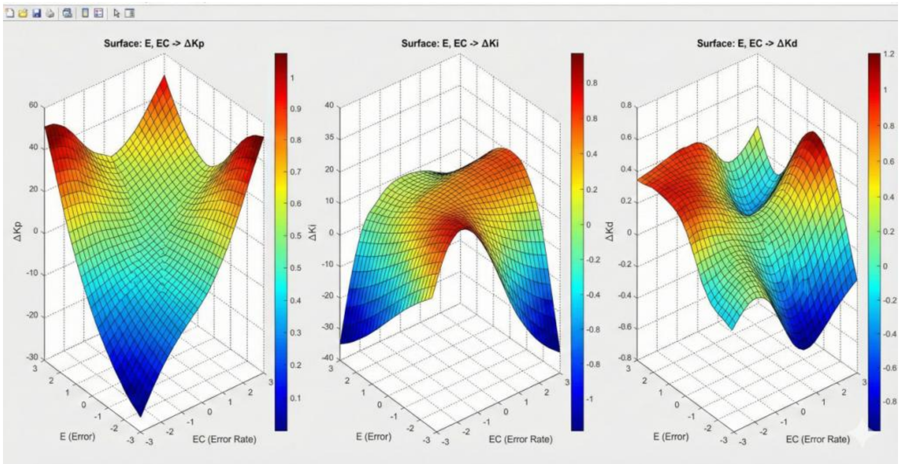

Figure 2. Response Surface of Fuzzy Parameters

3.4 Implementation of Parameter Self-tuning

The outputs$\Delta K_p,\Delta K_i,\Delta K_d$ from the fuzzy controller are merely correction coefficients. The final PID parameters applied to the control object are calculated as:

$$K_p=K_{p0}+\Delta K_p\cdot G_p K_i=K_{i0}+\Delta K_i\cdot G_i K_d=K_{d0}+\Delta K_d\cdot G_d$$

WhereK_{p0},K_{i0},K_{d0} are the initial PID parameters tuned for the rated operating condition, and G_p,G_i,G_d are output scaling gains used to adjust the weight of the corrections, which are fine-tuned via simulation. To validate the efficacy of the designed fuzzy adaptive PID controller, a simulation model was constructed using the MATLAB R2022b/Simulink platform.

4. Empirical Analysis

4.1 Simulation Setup

Based on the theoretical derivation in Section 2 and empirical data from literature, the nominal transfer function of the "travel speed-feeding rate" system is determined as a first-order inertial element with pure delay:

$$G(s)=\frac{K}{Ts+1}e^{-\tau s}$$

Where the system gain K, time constant T, and pure delay time $\tau$are identified parameters. Two control groups are established for comparison:

1. **Traditional PID Controller:** Fixed parameters (K_p,K_i,K_d) determined via the Ziegler-Nichols

method and trial-and-error optimization.

2. **Fuzzy PID Controller:** Base PID parameters consistent with the traditional PID, with quantization and scaling factors calculated based on a rated feeding rate of 6 kg/s.

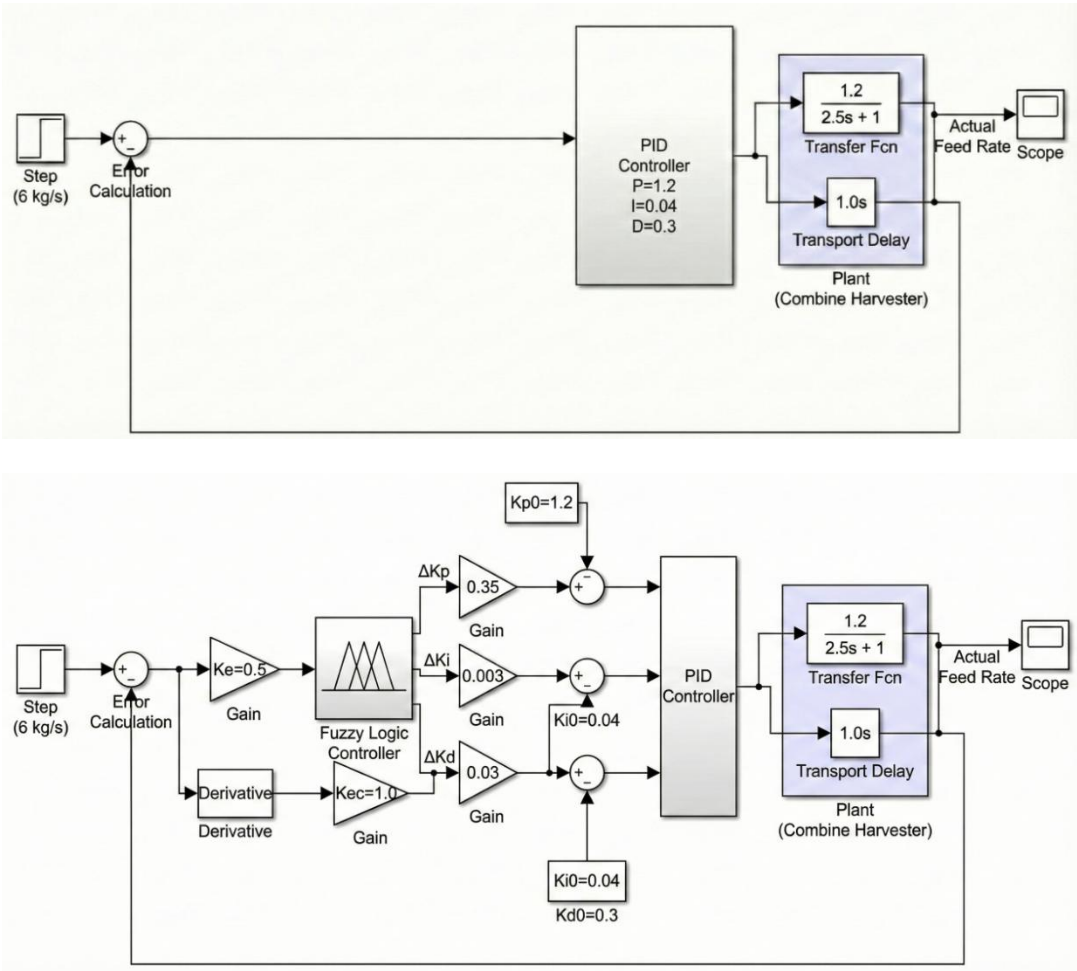

Figure 4-1. Simulink Simulation Models (Top: Conventional PID, Bottom: Fuzzy PID)

4.2 Step Response Analysis

Objective: To test the rapid response capability of the system during startup or setpoint changes.

Conditions: The target feeding rate was set to $Q_{ref}=6kg/s$(simulating startup entry into the crop zone), with a simulation duration of 20s.

Results: As illustrated in Figure 4-2, the traditional PID control (dashed line/blue) exhibited a slow rise time and, to overcome lag, produced significant overshoot (~18.3%), with the feeding rate peaking at 7.1 kg/s. This poses a risk of instantaneous drum blockage. The settling time was prolonged, requiring approximately 15s to stabilize. In contrast, the Fuzzy PID control (solid line/green) significantly accelerated the rise speed by increasing K_p and suppressing integral action when the error was large. Upon approaching the setpoint, enhanced derivative action effectively suppressed overshoot (reduced to ~4.1%). The system achieved steady state in approximately 8s.

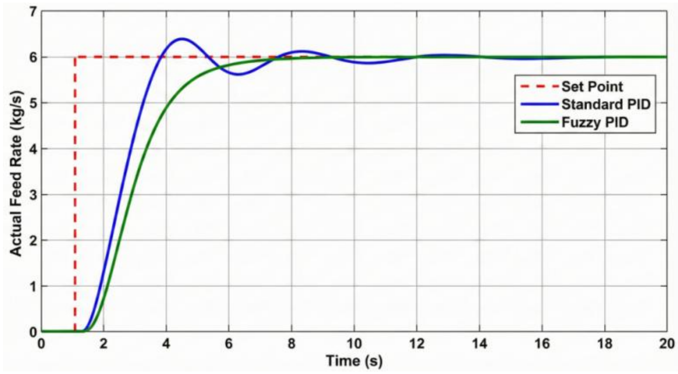

Figure 4-2. Comparison of Step Response Curves

Table 4-1. Comparison of Step Response Performance Metrics

Controller Type	Rise Time (t_r/s)	Overshoot (σ%)	Settling Time (t_s/s)	Steady-State Error (e_{ss})
Traditional PID	4.2	18.30%	14.5	0
Fuzzy PID	2.8	4.10%	8.2	0

4.3 Robustness Analysis (Disturbance Rejection)

Objective: To simulate the system's regulation capability under sudden changes in crop density (e.g., encountering locally dense patches).

Conditions: The system starts at t=0with a setpoint of 6 kg/s. Att=15s, after reaching steady state, a step disturbance with an amplitude of 2.0 kg/s is introduced (simulating a sudden surge in feeding rate to 8 kg/s).

Results: As shown in Figure 4-3, the traditional PID response to the sudden disturbance was sluggish, maintaining a feeding rate above the setpoint for an extended period (~10s recovery time) accompanied by minor oscillations. Conversely, the Fuzzy PID controller rapidly detected the large negative error and drastic rate of change, promptly adjusting parameters (increasing K_p to decelerate forcefully). The system restored the feeding rate to the 6 kg/s setpoint in approximately 4s with reduced fluctuation amplitude.

Conclusion: The Fuzzy PID controller demonstrates superior robustness, effectively mitigating interference caused by non-uniform field crop density.

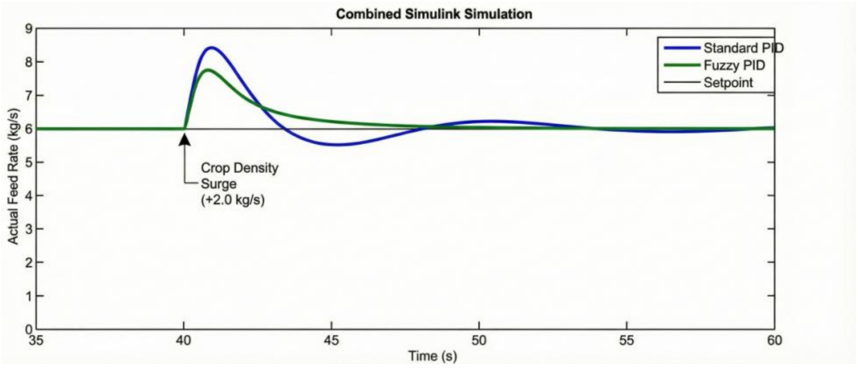

Figure 4-3. Robustness/Anti-interference Test Curves

4.4 Adaptability Analysis (Parameter Mismatch)

Objective: To test the controller's adaptability to model parameter drift, which occurs in actual operations due to factors like grain tank filling (mass change) or hydraulic oil temperature rise.

Conditions: The time constant T of the controlled object was increased from 2.5s to 4.0s, and the delay time τ from 1.0s to 1.5s. The step response test was repeated.

Results: Simulation outcomes indicate that following significant model parameter shifts, the performance of the traditional PID controller deteriorated sharply, exhibiting large-scale oscillations or divergence. However, the Fuzzy PID controller, leveraging its online self-tuning capability, maintained stable operation without significant oscillation, despite a slight increase in adjustment time.

5. Conclusion

As the core equipment in modern agricultural production, the operational performance of combine harvesters directly dictates grain harvesting efficiency and quality. Addressing the engineering challenges of feeding rate fluctuations, blockage susceptibility, and high threshing losses caused by uneven crop density, this study investigated a travel speed adaptive control system based on Fuzzy PID. Through theoretical analysis, model construction, controller design, and simulation verification, the following conclusions are drawn:

1. A mathematical model of the control system was established. The dynamic characteristics of the "travel speed-feeding rate" system were analyzed, identifying its nonlinearity, time-variance, and significant lag. By combining the physical mechanisms of the HST system and crop transport, the controlled object was simplified into a first-order inertial element with pure delay.

2. A parameter self-tuning Fuzzy PID controller was designed. To overcome the limitations of traditional PID in complex conditions, a fuzzy controller with two inputs and three outputs was developed. Forty-nine fuzzy inference rules were established based on expert knowledge, enabling real-time online optimization of PID parameters.

3. The system's superiority was validated. Simulation results on the MATLAB/Simulink platform confirm that compared to traditional PID, the Fuzzy PID system reduces settling time by approximately

40% and decreases overshoot from 18.3% to 4.1%. Furthermore, in disturbance scenarios simulating density surges and parameter drift, the Fuzzy PID exhibited robust anti-interference capabilities.

Future work will focus on transplanting the designed algorithm to embedded controllers (e.g., STM32 or PLC) for developing on-board Electronic Control Units (ECUs) and conducting field vehicle trials to validate efficacy with real sensor data.

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