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Research Paper

Research on intelligent maize targeted fertilisation method based on BPNN PID adaptive position feedback regulation

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ABSTRACT

Given problems, such as low accuracy of fertiliser application control, large positioning errors, and poor fault monitoring effects in targeted fertilisation operations, this study proposes an intelligent maize-targeted fertilisation method based on a Backpropagation Neural Network (BPNN) Proportional-Integral-Derivative (PID) adaptive position feedback regulation. With the STM32 microcontroller as the master-slave controller, an intelligent maize-targeted fertilisation system was developed through the design of multi-sensor fusion, control parameter calculation and optimisation, construction of a fertilisation drive device, and fault monitoring system. BPNN PID adaptive optimisation was used to control the angular displacement of the fertiliser applicator, and automatic control technology drove the targeted fertilisation mechanism. By integrating dual photoelectric sensors to detect the target maize, an encoder collects the angular displacement of the fertiliser applicator, a ranging sensor monitors the fertiliser amount in the fertiliser box, a pressure sensor monitors the status of the fertiliser pipe, a positioning sensor monitors the operation speed, and multi-machine communication processes the fertilisation operation data. Targeted control and fault monitoring of fertilisation operations under multi-sensor fusion were realised. The adjustment time of the optimisation algorithm is 0.9 s, and the response is fast. Experiments show that the accuracy of fertiliser application control is greater than 95 %, the average positioning error of fertilisation is less than 28.1 mm, the fault alarm success rate reaches 97 %, and the average response time of fault alarm is less than 0.45 s. The intelligent maize-targeted fertilisation method in this study can achieve precise fertilisation control in maize-targeted fertilisation operations.

Nomenclature	
Abbreviations	
BPNN	Backpropagation Neural Network
GNSS	Global Navigation Satellite System
PID	Proportional-Integral-Derivative
PWM	Pulse Width Modulation
PLC	Programmable Logic Controller
Symbols	
A	Target angular displacement of fertiliser applicator rotation,rad;
B	Target fertiliser application,g;
b	Actual fertiliser applied,g;
c	Accurate number of fault alarms
D	Number of tests
D_1	Maize spacing,m
D_2	Maize diameter,m
d_1	Distance between two maize detection sensors,m
d_2	Distance between fertiliser baffles and maize detection device 2,m
$e(t)$	Fertiliser amount error at time t,g
f_1、f_2、f_3	frequency of sensors, controllers, and electromagnets,Hz
g	Acceleration of gravity,m s^{-2}
H	Fertiliser tank height,m
h_1	Distance between fertiliser applicator and fertiliser barrier,m
K_p、K_i、K_d	Proportional, integral, and differential parameters
L	Distance from top of fertiliser tank to fertiliser tank,m
l	Absolute error value of fertilisation position,mm
N	Fertiliser surplus,%
N_b	Fertilisation quantity control precision,%
N_C	Accuracy rate of fault alarm,%
N_l	Relative error value of fertilisation position,mm
N_t	Average response time of fault alarm,s
$r(t)$	Target fertilisation amount at time t,g
t	Fault alarm response time,s
t_1	Amount of time it takes the fertiliser to fall into the baffle,s
t_2	Opening time of the fertiliser baffle,s
V	Speed at which the tractor travels, m s^{-1}
$V_{(max)}$	Maximum speed at which the tractor travels,m s^{-1}
$V_{(min)}$	Minimum angular speed set by the applicator,rad s^{-1}
$y(t)$	Actual amount of fertiliser applied at time t,g

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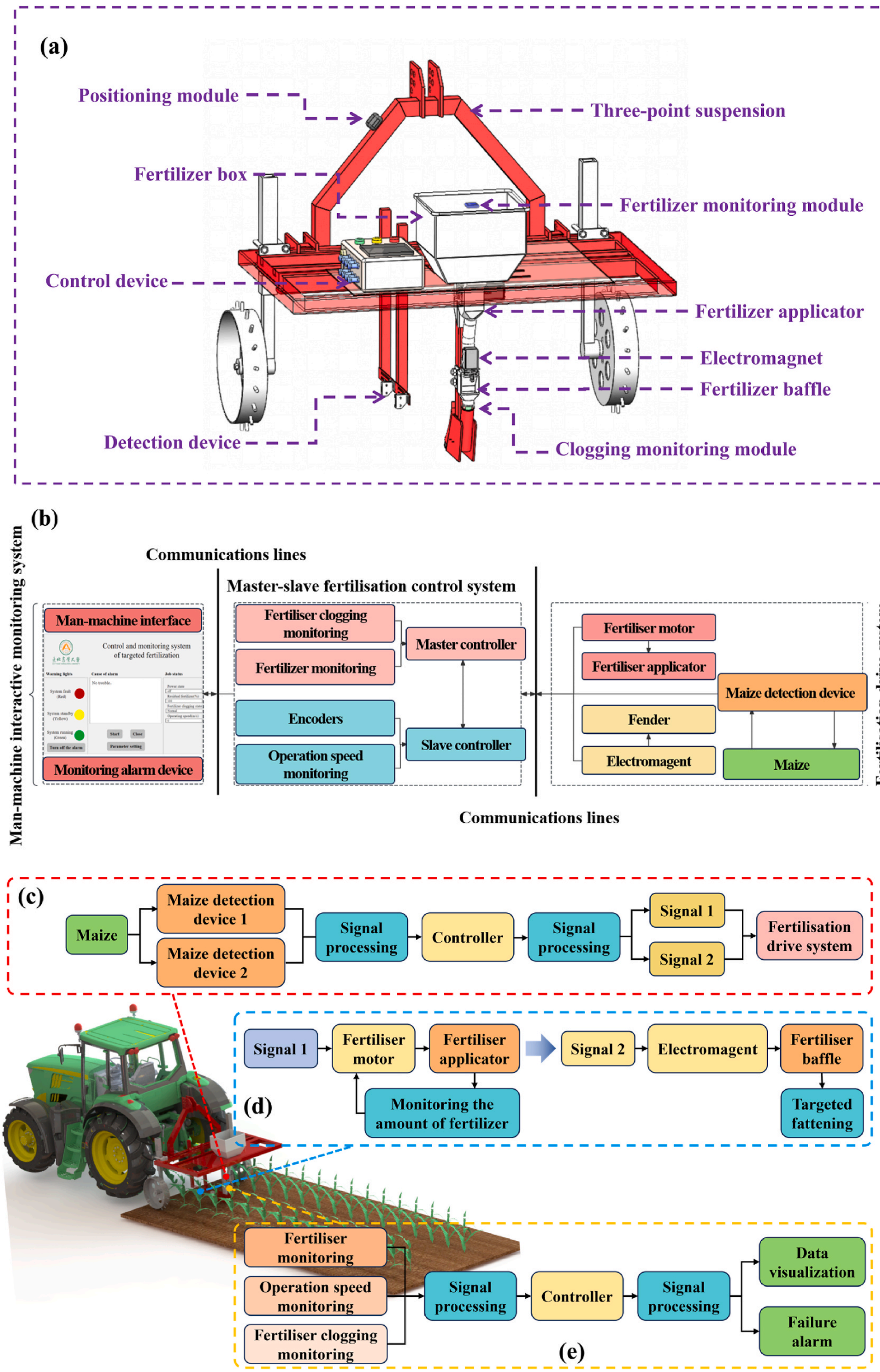

Fig. 1. Intelligent maize-targeted fertilisation system: (a) Overall structure of targeted fertilisation system; (b) General operational flow of the targeted fertilisation system, including signal reception, decision-making, and fertilisation control; (c) Dual-sensor maize detection system generating sequential signals; (d) Drive system executing fertiliser delivery and release; (e) Fault monitoring module detecting tube blockage, fertiliser shortage, and abnormal speed.

1. Introduction

Maize (*Zea Mays*), one of the most world's important food crops, has become a crucial raw material for the livestock, industrial, and bioenergy sectors (Li et al., 2017), and it plays a vital role in sustainable agricultural development. Fertilisation is a key aspect of crop cultivation management and affects the final crop yield (Hüttel et al., 2022). Traditional fertiliser strip application techniques result in decreased fertilisation quality and cause serious negative environmental impacts due to excessive fertilisation (Lv et al., 2020). Therefore, the proposal of targeted fertilisation technology to achieve fertilisation at specific locations is crucial for improving the quality of fertilisation operations (Khamarunneesa et al., 2023). Investigating intelligent targeted fertilisation methods based on targeted fertilisation technology is important to enhance the accuracy of fertilisation quantity control and positioning accuracy during targeted fertilisation operations.

Currently, research on targeted fertilisation technology mainly includes optimisation of the drive system and development of crop detection and fault monitoring systems. In terms of drive systems, numerous researchers have implemented closed-loop feedback control for the angular displacement and speed of fertiliser applicators, optimising the speed, angular displacement, and response speed of the fertiliser applicator using Proportional-Integral-Derivative (PID) algorithms. For example, Wang et al. (2022) developed a high-precision fertiliser flow control system, establishing a relationship model between fertiliser flow and capacitance output using capacitive sensors, and optimising the fertiliser application quantity of the system through PID algorithms, thus improving the accuracy of fertilisation quantity control. Yu et al. (2020) proposed a high-frequency targeted fertilisation system. To achieve stable and rapid fertilisation during high-frequency targeted fertilisation, the response speed of the fertiliser valve was optimised using PID algorithms. Zhang et al. (2021) introduced a PID closed-loop algorithm to adjust the speed of the fertiliser applicator to achieve a fast response and real-time precision fertilisation control. The experimental results showed that the accuracy of fertilisation quantity control of the control system was greater than 95 %. The above researchers observed through MATLAB/SIMULINK simulation results that PID algorithms improved the response speed of the control system. However, owing to the inability of PID algorithms to adaptively adjust the control parameters, they exhibited poor robustness and could not accurately fertilise complex and changing field environments.

Many researchers have also used deep learning combined with computer vision technology to improve the accuracy of crop detection and targeted fertilisation positioning. Zong and Liu (2021) utilised a maize-targeted fertilisation control system based on machine vision using visual technology and automatic control technology to drive the fertiliser applicator for targeted fertilisation after determining the target crop, thereby improving the detection accuracy and fertilisation positioning accuracy. Zhang et al. (2024) employed a fruit orchard target crop detection method based on machine vision, adapted the improved YOLOv5 deep-learning algorithm to an orchard environment identification task, and deployed it on a mobile terminal for target detection, achieving good detection accuracy and speed in complex environments. Currently, computer vision mostly adopts deep learning algorithms to detect target crops more accurately; however, the detection system requires a longer computation time. Therefore, detection systems using visual technology are lacking in terms of response speed and cost. Alternatively, other researchers have used sensors for the real-time detection of target crops to improve the response time of the system. Bai et al. (2021) proposed an automatic targeted fertilisation control system using a laser radar to monitor the target position in real time and generated Pulse Width Modulation (PWM) waveforms using STM32 microcontrollers to drive the fertiliser applicator for fertilisation operations, meeting the requirements of precise targeted fertilisation control. Compared to visual technology, real-time detection of target crops using sensors not only improves the response time but also significantly reduces costs. However, the detection accuracy is low in complex field environments, necessitating the improvement of the overall operational quality of the system through automatic control technology. Regarding fault monitoring systems, many researchers use various sensors to monitor and alarm operational faults, such as fertiliser leakage and fertilisation quantity, to improve fertilisation operation efficiency. Jin et al. (2020) proposed a smart vegetable fertilisation monitoring system using a Programmable Logic Controller (PLC) for control execution and an alarm for fertilisation blockage signals collected by piezoelectric film sensors. Wang et al. (2017) developed a fertilisation quantity monitoring system using sensors to detect the amount of fertiliser in the fertiliser box and indirectly obtain the current fertilisation quantity based on the rotational speed of the fertiliser discharge shaft obtained by the encoder. The field experiments showed that the fertilisation quantity monitoring error was less than 6.3 %. Liu et al. (2017) introduced a maize fertilisation monitoring system and designed a user interface based on the Ubuntu system to achieve real-time monitoring of fertilisation quantity and visualisation of fault alarms. However, current research lacks fault alarms for abnormalities, such as operating speed and fertiliser blockage, resulting in poor operational efficiency.

The above research has advanced the optimisation of the drive, crop detection, and fault monitoring subsystems in targeted fertilisation, providing valuable references for intelligent field applications. However, limitations remain, including inaccurate angular displacement control of the fertilisation drive, low detection accuracy, and slow response of the crop detection system under variable field conditions. To address these challenges, this study proposes an adaptive control strategy based on Backpropagation Neural Network (BPNN) PID position feedback regulation, combined with multi-sensor fusion. We hypothesise that this approach will improve real-time crop detection, enable rapid and precise applicator actuation, and provide timely fault monitoring, thereby enhancing operational accuracy, responsiveness, and stability. Compared with conventional fixed-parameter or single-sensor methods, it is expected to offer a more reliable and adaptable solution for precision maize fertilisation in complex field environments.

2. Materials and methods

2.1. Principle of intelligent maize-targeted fertilisation system

An intelligent maize-targeted fertilisation system is mounted on a tractor using a three-point suspension device. The entire system is composed of components for maize detection, drive control, and fault monitoring (Fig. 1a). A series of coordination processes, such as accurate identification, targeted fertilisation, and fault monitoring of each maize, are completed in turn. The entire system is divided into a targeted fertilisation control system, a targeted fertilisation drive system, a targeted fertilisation fault monitoring system, and a maize detection system. The targeted fertilisation control system adopts a master-slave controller structure, which is responsible for processing targeted fertilisation fault monitoring data (fertiliser tube blockage, missing fertiliser box, and abnormal operation speed) and maize information, as well as driving the targeted fertilisation control system (Fig. 1b). The maize detection system consists of two detection devices: maize detection device 1 and maize detection device 2. Two detection signals for the target maize are successively obtained through misplaced placement, and the signals are successively transmitted to the targeted fertilisation control system (Fig. 1c) to drive the targeted fertilisation drive system to complete specific targeted fertilisation actions. The targeted fertilisation drive system is composed of a fertilisation motor, fertiliser applicator, fertiliser discharge baffle, and an electromagnet. First, after signal 1 is transmitted to the fertilisation drive system, the fertiliser motor drives

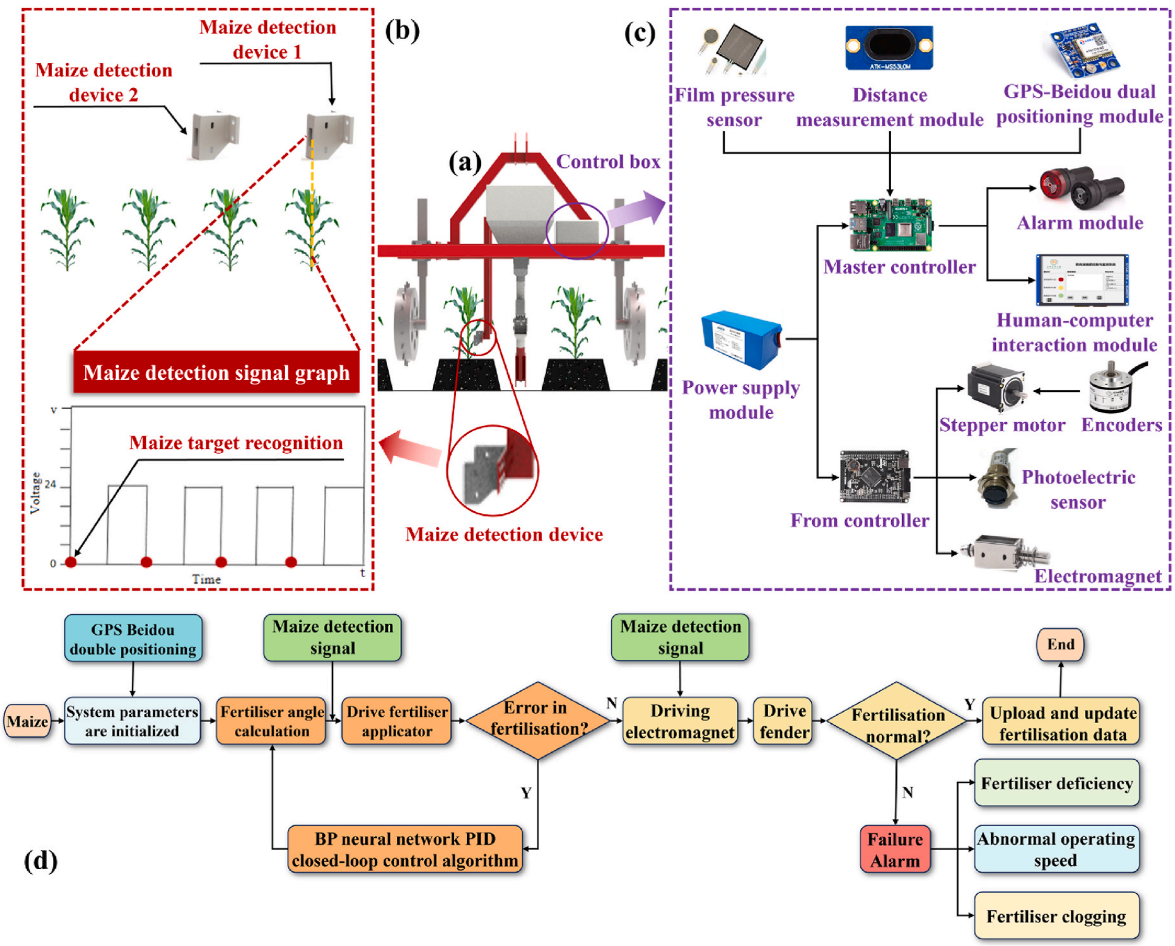

Fig. 2. Composition and working principle of intelligent maize-targeted fertilisation system: (a) Overall structure of the targeted fertilisation device; (b) Working principle of maize detection device; (c) Hardware composition of targeted fertilisation system; (d) Operational workflow of the targeted fertilisation system, including maize detection, fertilisation control, fault monitoring and alarm, and human–machine interaction.

the fertiliser applicator to transport the fertiliser to the fertiliser discharge baffle. Second, after signal 2 is transmitted to the fertilisation drive system, the electromagnet drives the fertiliser discharge baffle action to achieve the targeted fertilisation (Fig. 1d). The targeted fertilisation fault-monitoring system is integrated with various sensors to monitor the problems of fertiliser blockage in the fertiliser tube, fertiliser absence in the fertiliser box, and abnormal operation speed, and transmits the monitored data to the targeted fertilisation control system using a signal circuit to realise data visualisation and fault alarm (Fig. 1e).

2.2. Hardware composition of intelligent Core targeted fertilisation system

The intelligent maize-targeted fertilisation system mainly consists of fertilisation controllers (master controller and slave controller), a stepper motor, fertiliser baffle, fertiliser applicator, electromagnetic valve, encoder, photoelectric sensor, distance measurement module, film pressure sensor, GPS/Beidou dual positioning module, power supply module, human-computer interaction module, and alarm module (Fig. 2a and c). The fertilisation master and slave controllers realise the integrated control functions of maize detection, fertilisation drive, and fault monitoring of the targeted fertilisation system. The power supply module provides power supply for the targeted fertilisation system. The human-computer interaction module, through the fertilisation master controller, sets the target fertilisation quantity and monitors the status of targeted fertilisation operations in real-time. The stepper motor drives the fertiliser applicator and is connected to an encoder to provide real-time feedback on the actual fertiliser application amount to the fertiliser master and slave controllers. Both the maize detection devices use photoelectric sensors to detect target maize and generate voltage signals, which are transmitted to the fertilisation master-slave controller through signal circuits (Fig. 2b). Distance measurement module and film pressure sensor are placed at the upper end of the fertiliser box and the inner wall of the fertiliser tube, respectively, to monitor the fertiliser quantity in the fertiliser box and the fertiliser blockage in real-time. The alarm module is connected to the fertilisation master and slave controllers to emit alarm signals for fault information of targeted fertilisation operations. The GPS/Beidou dual positioning module collects the fertilisation operation speed in real-time and transmits it to the fertilisation master and slave controllers.

2.3. Optimisation design of intelligent maize-targeted fertilisation control process

During the targeted fertilisation operation process, when maize detection device 1 detects the target maize, the fertilisation controller utilises the BPNN PID closed-loop algorithm combined with the actual fertilisation quantity collected by the encoder to adaptively adjust the angular displacement of the fertiliser applicator (Priya et al., 2022), optimising the actual fertilisation quantity to the fertiliser baffle. The fertiliser baffle is driven by an electromagnetic valve, and when the maize detection device 2 detects maize, the fertiliser controller adjusts the conduction time of the fertiliser baffle according to the operating speed and target fertilisation quantity, thus achieving precise targeted

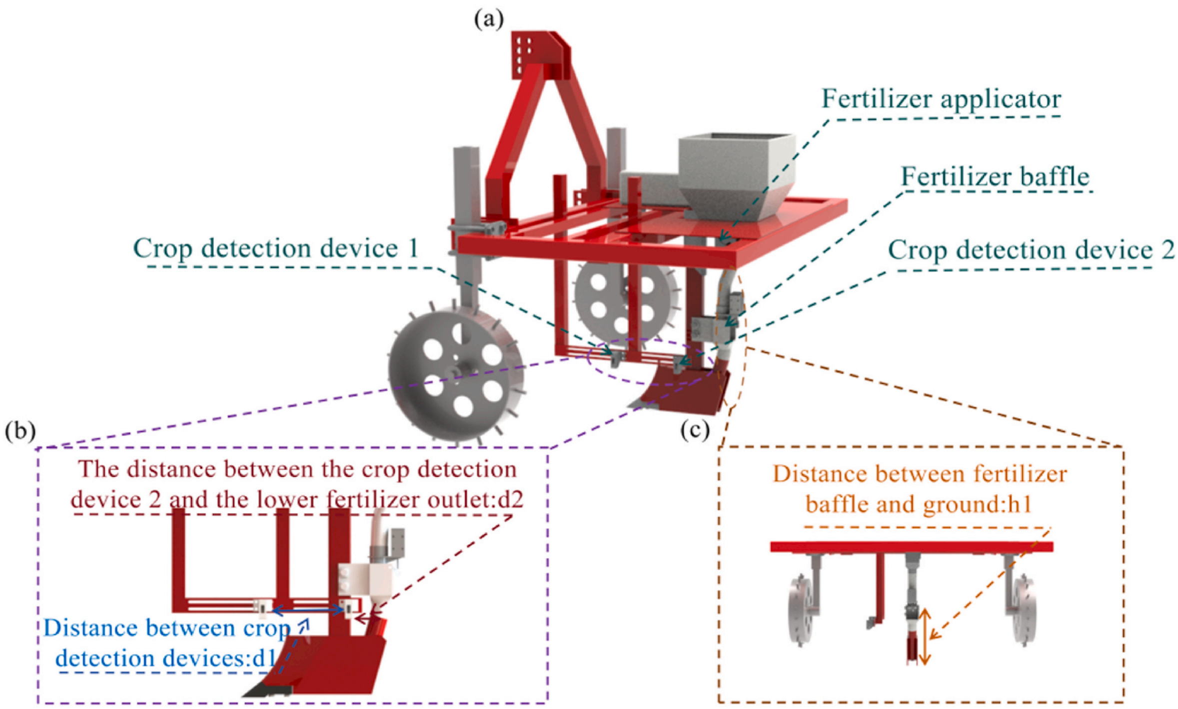

Fig. 3. Analysis of key parameters of targeted fertilisation drive mechanism: (a) Composition of targeted fertilisation drive mechanism; (b) Analysis of distance between maize detection devices and distance between maize detection devices and lower fertiliser outlet; (c) Analysis of distance between fertiliser baffles and ground.

fertilisation. In the event of faults, such as insufficient fertiliser in the fertiliser box, fertiliser tube blockage, or abnormal operating speed, the fertilisation controller processes various fault signals, and the alarm module visualises and alarms the faults (Fig. 2d).

2.3.1. *Determination of key parameters of targeted fertilisation drive mechanism*

This study designs a targeted fertilisation drive mechanism consisting of a fertiliser applicator, fertiliser baffle, and maize detection device (Fig. 3a). The targeted fertilisation drive mechanism, after detecting maize by maize detection device 1, drives the fertiliser applicator to deposit the target fertilisation quantity at the fertiliser baffle, waiting for the maize detection device 2 to detect maize again and drive the fertiliser baffle to deposit the target fertilisation quantity at the targeted fertilisation position, achieving precise targeted fertilisation. Analysis of the various parameters of the targeted fertilisation drive mechanism is as follows.

First, the distance from the fertiliser applicator to the ground is approximately 0.80 m, and theoretically, the closer the fertiliser baffle is to the ground, the better the targeted fertilisation effect. However, because of the presence of the furrow opener below, the distance h_1 between the fertiliser baffle and the ground is approximately 0.42 m (Fig. 3c). In both the benchtop and field experiments conducted in this study, the height of the fertiliser baffle above the ground is set at 0.42 m.

Subsequently, the calculation and analysis of the distance d_1 between the two maize detection devices (Fig. 3b) are performed to ensure that the two maize detection devices can sequentially drive the fertiliser applicator and fertiliser baffle to act after detecting the maize. According to the equation for free-fall descent, the time required for the fertiliser applicator to deposit the target fertiliser into the fertiliser baffle after maize detection device 1 detects the maize is expressed as follows:

$$h = \frac{1}{2}gt^2 \tag{1}$$

$$t_1 = \frac{\sqrt{2gh_1}}{g} \times \frac{30A}{\pi V_{(\min)}} \tag{2}$$

where g is the acceleration due to gravity, 9.8 m s^{-2}; h_1 is the distance between the fertiliser applicator and the upper end of the fertiliser baffle, m; A is the target position of the fertiliser applicator, rad; $V_{(min)}$ is the minimum set speed of the fertiliser applicator, rad s^{-1}; t_1 is the time required for the target fertiliser to be deposited at the lower end of the fertiliser baffle, s.

Once t_1 is calculated, the distance between the two maize detection devices can be obtained based on the vehicle speed and maize spacing, as follows:

$$D_1 > d_1 \geq t_1 \times V_{(\max)} \tag{3}$$

where D_1 is the maize spacing, mm; $V_{(max)}$ is the maximum operating speed, m s^{-1}; and d_1 is the distance between the two maize detection sensors, m.

Finally, the distance h_2 between the fertiliser baffle and maize detection device 2 (Fig. 3b) and the conduction time t_2 of the fertiliser baffle are calculated and analysed to accurately deposit the fertiliser at the target position. Considering the response frequencies of the maize detection sensor, controller, electromagnetic valve, and operating speed, the distance between the two devices can be expressed as follows:

$$d_2 = \frac{V}{f_1 \times f_2 \times f_3} \tag{4}$$

where f_1, f_2, and f_3 are the response frequencies of the sensor, controller, and electromagnetic valve, respectively, Hz; V is the operating speed, m s^{-1}, and d_2 is the distance between the fertiliser baffle and maize detection device 2, m.

The conduction time of the fertiliser baffle is calculated based on the vehicle speed and maize diameter as follows:

$$t_2 = \frac{D_2}{V} \tag{5}$$

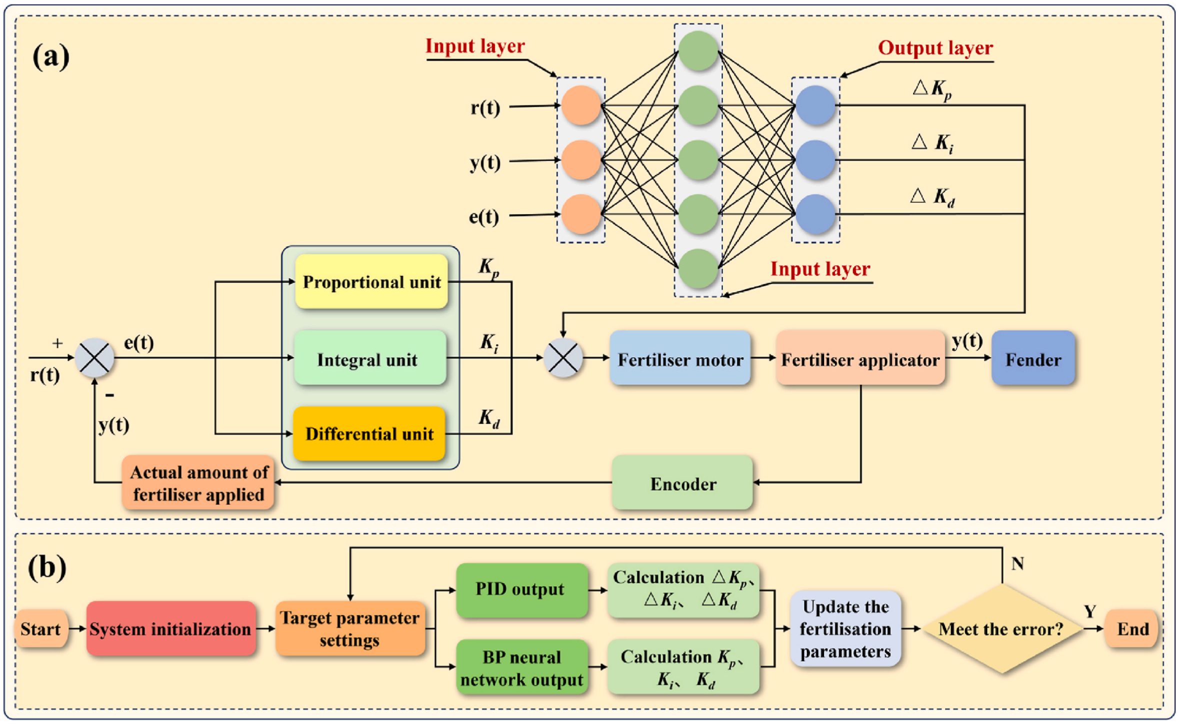

Fig. 4. Design of fertiliser application optimisation algorithm: (a) Principle of closed-loop control algorithm for fertiliser application based on BPNN PID; (b) Flowchart of the closed-loop control algorithm, where the iteration terminates when the relative fertilisation error $|e(t)|/r(t)$ is ≤ 10 % for two consecutive iterations.

where D_2 is the maize diameter, m; and t_2 is the opening time of the fertiliser baffle, s.

2.3.2. Design of fertilisation quantity optimisation algorithm based on adaptive position feedback adjustment

This study proposes a fertilisation quantity control strategy based on a BPNN–PID adaptive position feedback approach, designed to enhance real-time control accuracy and positioning precision in maize targeted fertilisation. While related control concepts have been reported, such as the PSO-BP-PID approach applied in orchard fertilisation (Wan et al., 2022), the method developed here differs substantially in algorithm structure, parameter self-tuning mechanism, and its adaptation to the operational demands of row-crop field environments. This control strategy consists of a BPNN controller and a PID controller, driving the fertiliser applicator to achieve an adaptive closed-loop feedback control of the fertilisation quantity (Fig. 4a). The BP neural network used in this study adopts a three-layer (3-5-3) network structure consisting of an input layer, a hidden layer, and an output layer. The input layer includes the expected value, actual value, and deviation. The encoder is used to obtain the actual fertiliser application amount in real-time as the actual value, and the theoretical fertiliser application amount is set as the expected value. Deviation is the difference between the expected and actual values. The number of neurons in the hidden layer is set to 5, and the learning rate and inertia factor are set to 0.2 and 0.05 respectively. The initial values of the weighting coefficients for the hidden and output layers are generated using a random function. The output layer corresponds to three parameters of the PID controller (proportional, integral, and differential coefficients).

The target fertilisation quantity and the actual fertilisation quantity are input into BPNN controller and PID controller for calculation (Fig. 4b) using the following steps.

(1) Calculate the fertilisation error $e(t) = r(t) - y(t)$ at time t.
(2) Normalise the target fertilisation quantity, actual fertilisation quantity, and fertilisation error, and use them as inputs to both the BPNN and the PID controller.
(3) Compute the outputs of each BPNN layer successively; the output layer yields the compensation values ΔK_p, ΔK_i, and ΔK_d for the incremental PID parameters.
(4) Calculate the control output $u(k)$ of the incremental PID controller and combine it with the BPNN controller output.
(5) Update the weighting coefficients of the hidden and output layers of the BPNN.
(6) Recalculate the fertilisation error $e(t)$ using the updated control parameters, and repeat Steps 2–5 until the relative error $|e(t)|/r(t)$ is less than or equal to 10 % for two consecutive iterations.

The intelligent maize-targeted fertilisation system uses BPNN PID adaptive optimisation control parameters to reduce the error between the target and actual fertilisation quantities (Tran et al., 2018). To verify the effectiveness of the BPNN PID fertilisation quantity closed-loop control (Zhang et al., 2023), a simulation model is built in MATLAB/Simulink (MathWorks, Natick, Massachusetts, United States) for analysis (Fig. 5a). To improve the simplicity and readability of the simulation model, complex logic is encapsulated into subsystem modules, namely the input submodule, fine molecule module, and motor submodule. The input submodule encapsulates the parameters required for control (including the controller output, controlled object output, actual input, and error) and implements a signal delay function through the Unit Delay module to ensure system stability and accuracy. The stepper motor is influenced by low-frequency oscillations. By subdividing the driving control, the angle of each step of the motor is reduced, thereby reducing the low-frequency oscillation phenomenon of the motor. Therefore, based on the driving-control principle, a subdivision module is built using Simulink. In this study, a two-phase hybrid stepper motor is used as the control object, and a motor subsystem module is built. To simplify the mathematical model of the motor (Zhong et al., 2016), the effects of stator pole-to-pole and end leakage, permanent magnet circuit leakage, hysteresis and eddy current,

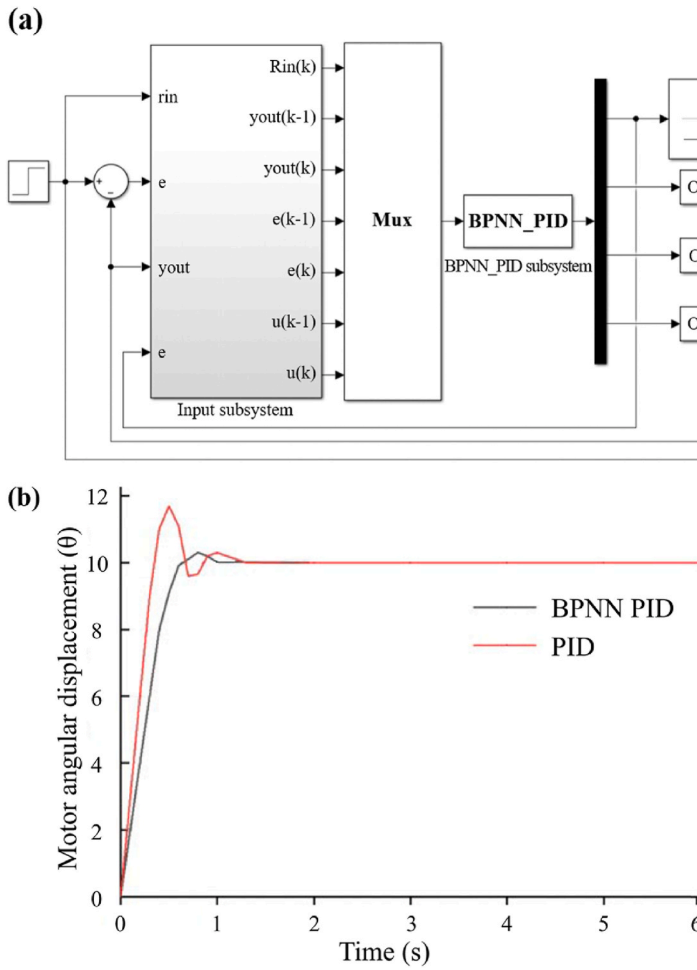

Fig. 5. Simulation design of fertiliser application optimisation algorithm: (a) Simulink simulation models of BPNN PID and traditional PID; (b) Step response simulation curve of optimisation algorithm.

saturation, and harmonic components of the stator coil self-inductance are not considered. In addition, various functions and languages in MATLAB are used to write M-functions, forming S-functions for closed-loop control optimisation functions, and the S-function function module in Simulink is used to connect MATLAB and Simulink. A system response curve is obtained under the condition of an input angular displacement of 10 rad (Fig. 5b).

2.4. Design of intelligent maize-targeted fertilisation fault monitoring system

The targeted fertilisation fault monitoring system is a critical function of the intelligent maize-targeted fertilisation system (Fig. 6a), achieving an alarm and visualisation display of the targeted fertilisation operation faults (Ji et al., 2021; Xie et al., 2021). The fault alarm function implemented in this study is based on monitoring functions, such as fertiliser pipe blockage, insufficient fertiliser in the fertiliser box, and abnormal operation speed, achieving fault alarms during targeted fertilisation operations (Fig. 6b). Therefore, the monitoring alarm function can quickly troubleshoot faults, thereby improving the efficiency of the targeted fertilisation operations.

First, the pressure module is placed on the four walls of the fertiliser pipe to monitor the pipeline status in real-time (Fig. 6c). When there is an abnormal blockage of the fertiliser in the fertiliser pipe and the fertiliser cannot fall, an alarm signal is triggered. To solve the difficulty in distinguishing between normal and abnormal fertiliser flow due to the high sensitivity of the pressure module, a combination of hardware and software is used to achieve a high-precision real-time monitoring function. In terms of hardware, owing to the relatively small force exerted on the pressure sensor by the fertiliser during normal flow compared to blockage, this study selects a pressure sensor with an appropriate pressure range based on the magnitude of the force. In terms of software, a logic code is added to the program. When a fertilisation operation occurs, the system judges whether the inner wall of the fertiliser pipe continues to exceed the critical value of the set pressure through the timing behaviour. If the pressure value of the inner wall of the fertiliser pipe still exceeds the critical pressure value after exceeding the blocking critical time, it indicates that there is an abnormal fertiliser blockage in the fertiliser pipe during the fertilisation process. Secondly, the GPS/Beidou dual-positioning module obtains the speed of the fertilisation operations (Fig. 6d), uploads the speed data to the control system for processing, and alerts the operator to any abnormal speed of the targeted fertilisation operations through an alarm device. Finally, the distance measurement module is placed at the top of the fertiliser box (Fig. 6e) to obtain the real-time distance from the top of the fertiliser box to the fertiliser inside it. The distance can be converted into the remaining amount of fertiliser in the fertiliser box (Eq. (6)) and visualised as a percentage through the human-computer interaction interface. When the fertiliser in the fertiliser box is below a critical value, the system triggers an alarm to remind the operator to refilll.

$$N = \left(1 - \frac{L}{H}\right) \times 100\% \tag{6}$$

where N is the remaining amount of fertiliser in the fertiliser box, %; H is

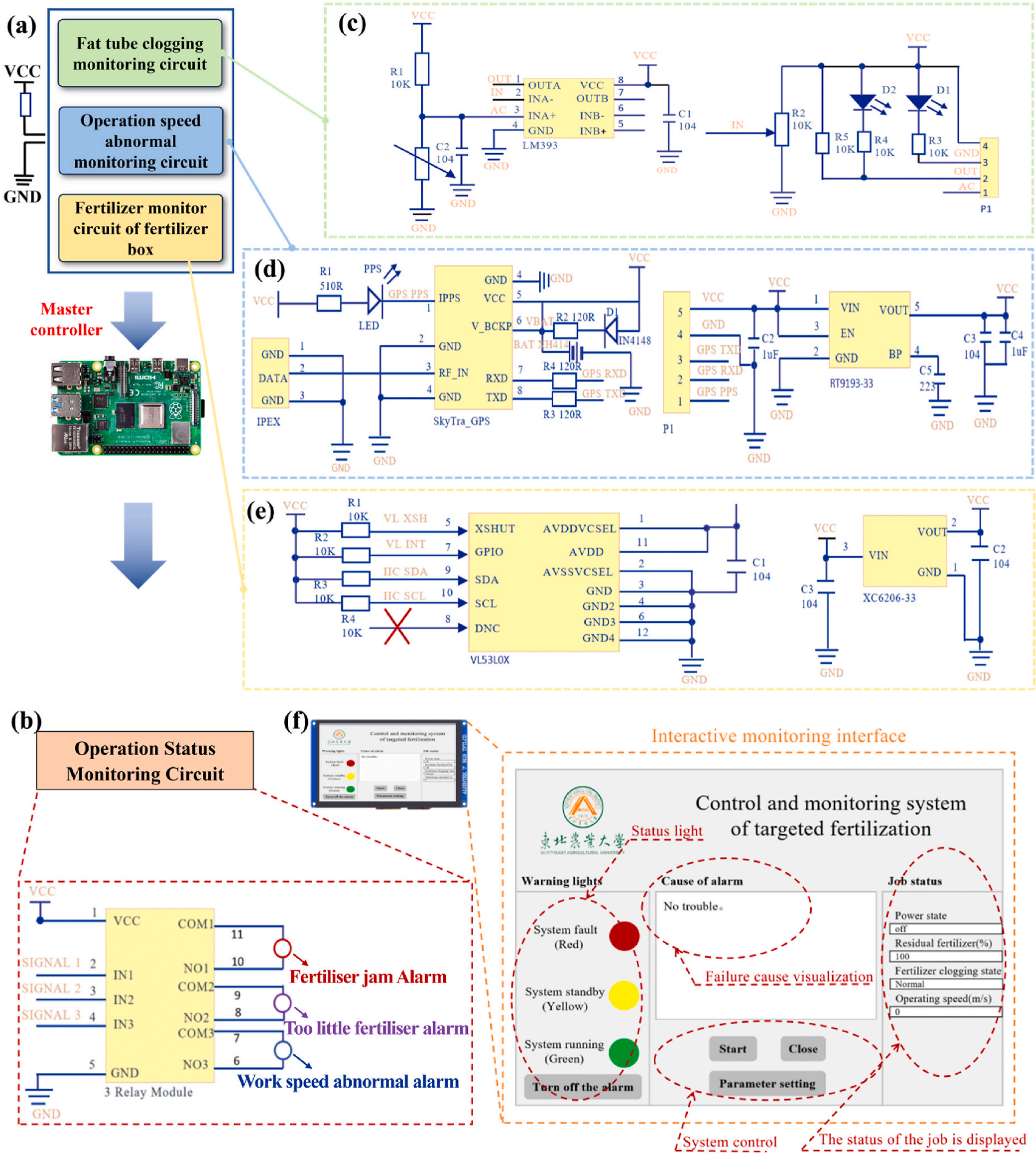

Fig. 6. Design of intelligent maize-targeted fertilisation fault monitoring system: (a) Design of targeted fertilisation monitoring circuit; (b) Design of fault alarm circuit; (c) Design of fertiliser blockage monitoring circuit; (d) Design of abnormal operation speed monitoring circuit; (e) Design of fertiliser box fertiliser monitoring circuit; (f) Human-machine interaction interface design.

the height of the fertiliser box, m; L is the distance between the top of the fertiliser box and the fertiliser in the fertiliser box ($0 =< L \leq H$), m.

Using the Ubuntu system, a targeted fertilisation fault monitoring user interface is developed in QT5.12.9 compilation environment (Fig. 6f). The user interface includes functions such as parameter settings, system operation status display, and fault alarm. Through the parameter setting button, parameters such as target fertilisation quantity, initialisation of operation speed, and the opening time of the fertiliser barrier can be set. The green light in the warning light column indicates that the targeted fertilisation system is running normally, and the system operation status column will display targeted fertilisation information. When the targeted fertilisation system encounters abnormal conditions (such as fertiliser blockage, fertiliser shortage, and abnormal operation speed), the red light in the warning light interface will light up, and the interface will display the specific abnormal reason. The yellow light in the warning light interface indicates that the targeted fertilisation system is in standby mode. The targeted fertilisation fault monitoring user interface has strong human-computer interaction and real-time characteristics, enabling real-time display of operation status for better control by operators.

2.5. Performance verification test of intelligent maize-targeted fertilisation system

2.5.1. Experimental method

Performance verification tests are conducted on a test bench to verify the performance of the intelligent maize-targeted fertilisation system. The test bench is developed by the School of Engineering, Northeast

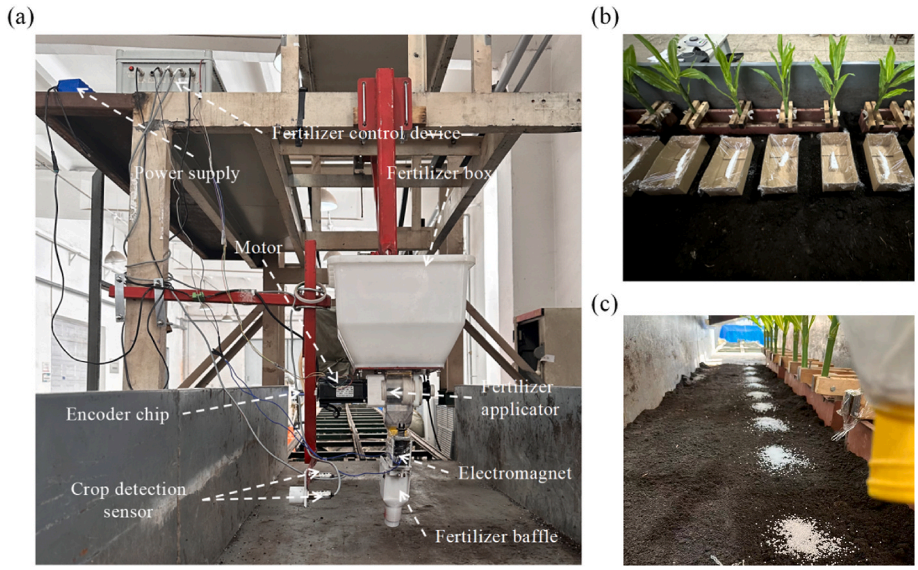

Fig. 7. Bench test of intelligent maize-targeted fertilisation system: (a) Test bench comprising applicator, control and detection units, and conveyor for simulated plant passage; (b) Application-rate accuracy test under operating speeds of 0.6, 0.8, and 1.0 m s^{-1} with target doses of 5.3, 10.6, and 15.9 g plant^{-1}; (c) Position-error test conducted under the same speed and target-dose conditions as in (b).

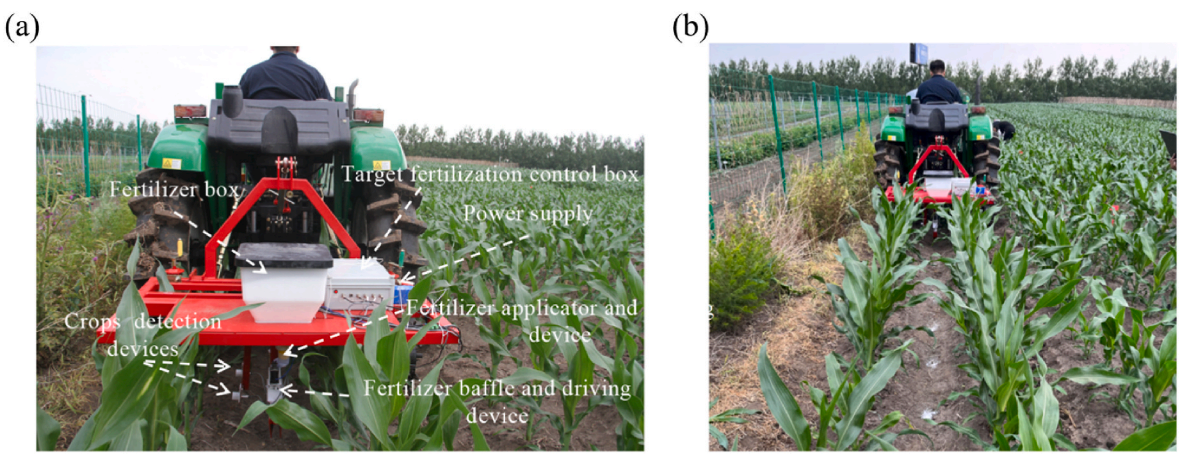

Fig. 8. Field testing of the intelligent maize targeted-fertilisation system: (a) Composition of the intelligent maize targeted-fertilisation system in the field tests; (b) Position-accuracy test at an application rate of 5.3 g plant^{-1}, with 50 repetitions at each operating speed of 0.6, 0.8, and 1.0 m s^{-1}.

Agricultural University, Harbin, Heilongjiang Province, China and mainly included devices such as intermittent fertiliser dispensers, fertiliser boxes, fertilisation motors, targeted fertilisation control devices, frequency converters, and conveyor beds (Fig. 7a). During the testing, the fertilisation operation speed is set to 0.6, 0.8, and 1.0 m s^{-1}, and the fertilisation quantity is set to 5.3, 10.6, and 15.9 g plant^{-1}. With fertilisation operation speed and quantity as influencing factors, experiments on the intelligent maize-targeted fertilisation system are conducted. Under different fertilisation operation speeds and quantities, the actual fertilisation quantity and fertilisation position error of the targeted fertilisation operation are recorded (Fig. 7b and c), and the experimental results are evaluated based on the fertilisation quantity control accuracy and fertilisation position accuracy.

To verify whether the intelligent maize-targeted system can accurately and promptly identify and alert the operator in the case of fertiliser blockage, fertiliser shortage, and abnormal operation speed, faults such as fertiliser pipe blockage, insufficient fertiliser in the fertiliser box, and abnormal operation speed are simulated. During the targeted fertilisation operation, the ranging module in the fertiliser box and pressure module in the fertiliser pipe are manually covered to simulate fertiliser shortage and fertiliser blockage anomalies. Owing to the absence of Global Navigation Satellite System (GNSS)signals indoors, the operating speed is manually adjusted to abnormal speeds to simulate abnormal operating speed faults. One hundred repetitions of each of the above three fault simulation tests are conducted to observe whether the buzzer flashed, whether the human-machine interface displayed reminders, and to record the fault alarm response time.

Field experiments are conducted at the Xiangyang Farm in Harbin (Heilongjiang Province) to verify the targeted fertilisation effects of the intelligent maize-targeted fertilisation system. A targeted fertilisation control box is placed in the main frame to realise the control function of the intelligent maize-targeted fertilisation system. The fertiliser barrier and its drive device are installed at the lower end of the fertiliser applicator and drive device to achieve targeted fertilisation operations. Two maize detection devices are installed on one side of the fertiliser barrier to detect the target maize. The pressure module, ranging module, and GPS/Beidou dual positioning module are respectively installed in the fertiliser pipe, fertiliser box, and control box, to realise fault monitoring and alarm functions during targeted fertilisation operations (Fig. 8a). During the field targeted fertilisation operations, 50

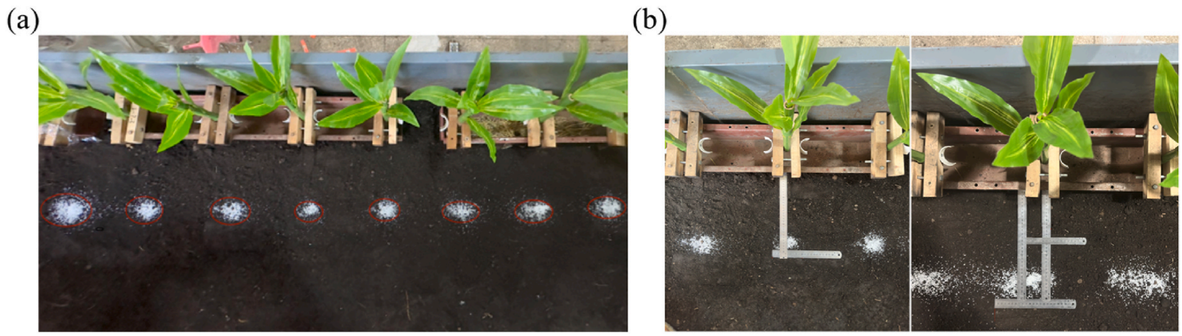

Fig. 9. Bench test for targeted fertilisation positioning accuracy: (a) Overhead view of the bench test following targeted fertilisation showing the location of the targeted fertilisation relative to the maize plans; (b) Photograph of the measurement process for targeted fertilisation error of maize plants.

repetitions were performed at each operating speed of 0.6, 0.8, and 1.0 m s^{-1} with an application rate of 5.3 g plant^{-1}, and the fertilisation position error was recorded. The field test results are evaluated based on the accuracy of the fertilisation position. The field test site is shown in Fig. 8b.

2.5.2. Data statistics and processing

After the targeted fertilisation verification tests, manual detection methods are used to record the fertilisation position error and fertilisation quantity of individual maize plants. By observing whether fault alarms occurred, the number of accurate fault alarms and fault-alarm response time are recorded. Referring to GB/T35487 "Variable fertiliser Seeder Control System", fertilisation quantity control accuracy, fertilisation position accuracy, and fault monitoring accuracy are selected as test indicators (Zong & Liu, 2021). The equations for calculating the test indicators are expressed as follows:

$$N_b = \left[1 - \frac{\sum |b - B|}{B \cdot b}\right] \times 100\% \tag{7}$$

$$N_l = \frac{\sum l}{d} \tag{8}$$

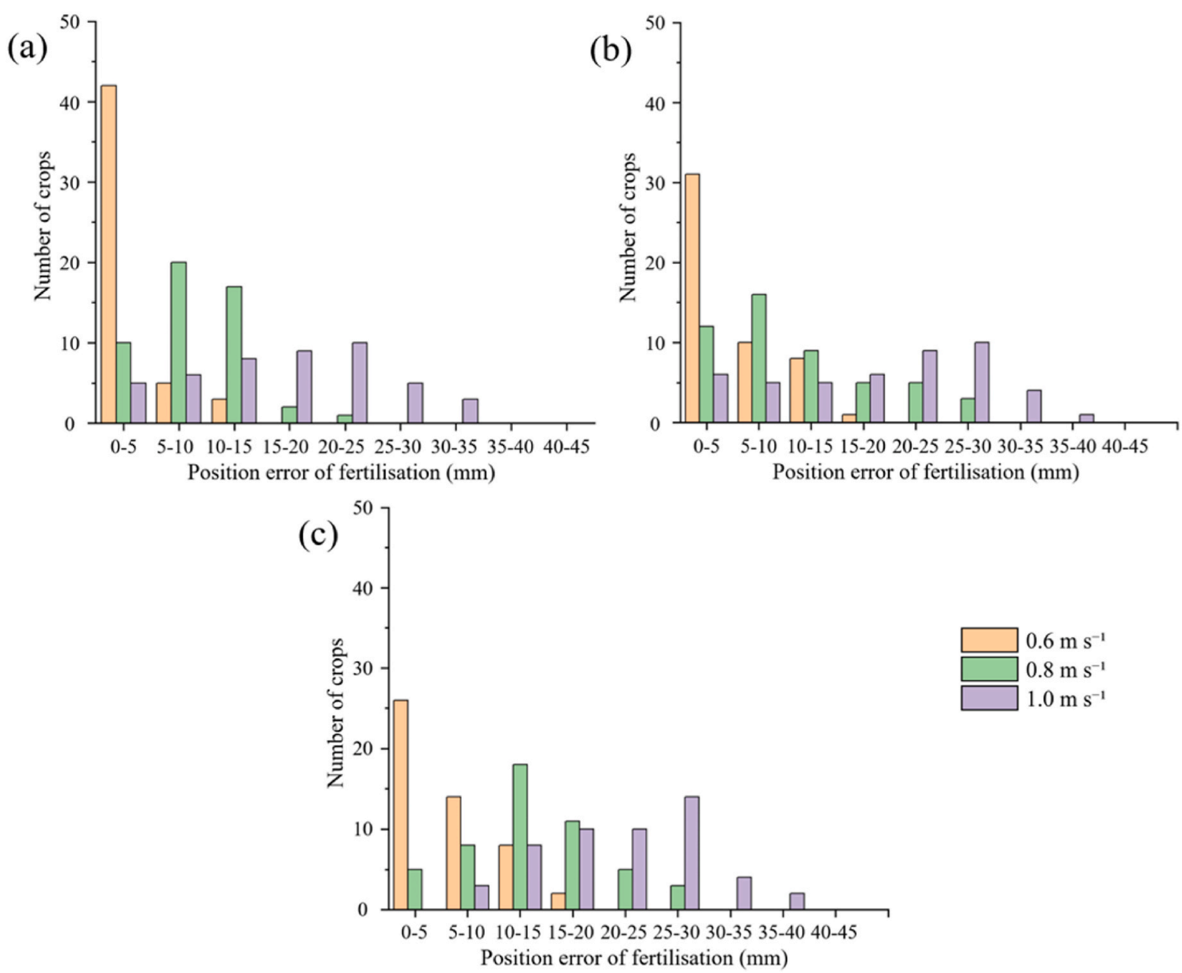

Fig. 10. Column chart of fertilisation position error of maize plants: (a) Fertilisation amount is 5.3 g plant^{-1}; (b) Fertilisation amount is 10.6 g plant^{-1}; (c) Fertilisation amount is 15.9 g plant^{-1}.

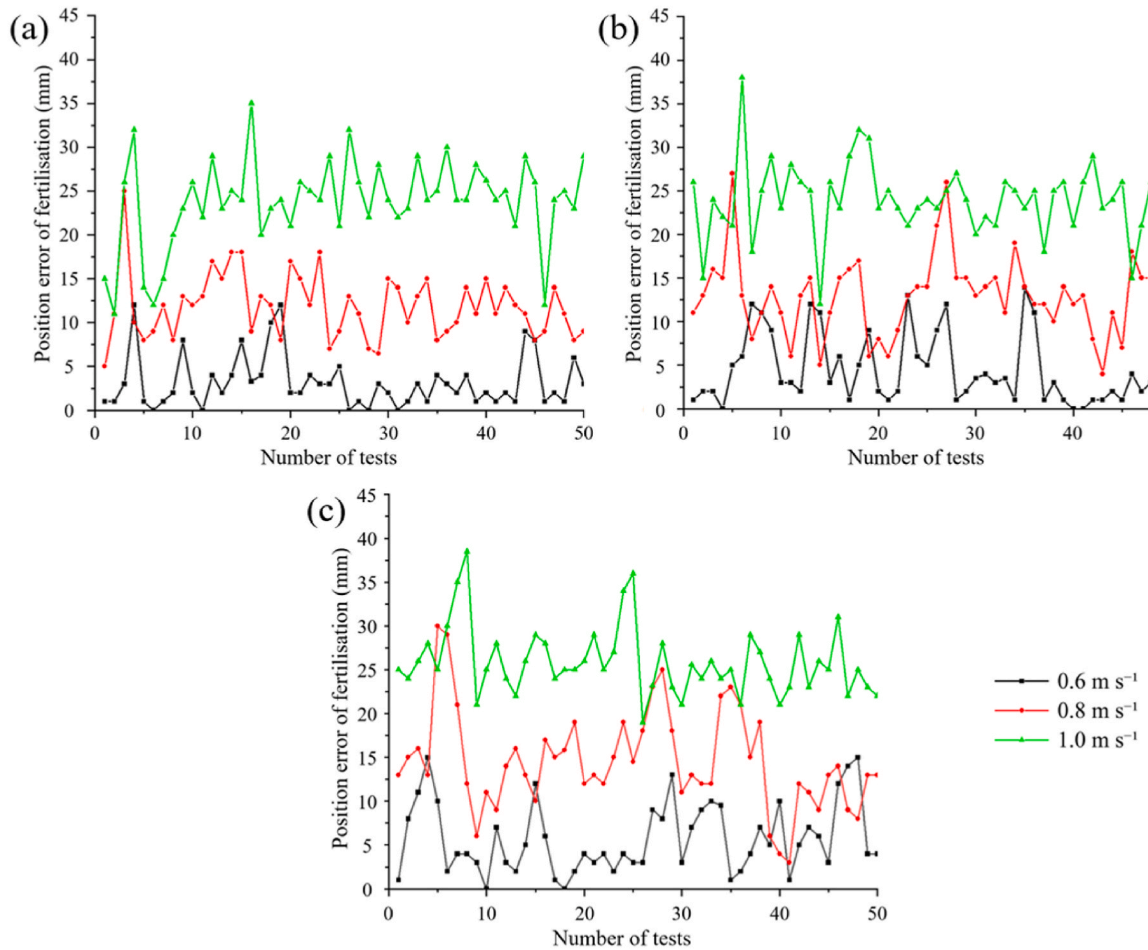

Fig. 11. Line graph of fertilisation position error of maize plants: (a) Fertilisation amount is 5.3 g plant^{-1}; (b) Fertilisation amount is 10.6 g plant^{-1}; (c) Fertilisation amount is 15.9 g plant^{-1}.

$$N_C = \frac{\sum c}{d} \times 100\% \tag{9}$$

$$N_t = \frac{\sum t}{d} \tag{10}$$

where N_b is the fertilisation quantity control precision, %; N_l is the relative error value of the fertilisation position, mm; N_c is the accuracy of the fault alarm, %; N_t is the average response time of the fault alarm, s; b is the actual fertilisation quantity, g; B is the target fertilisation quantity, g; l is the absolute error value of the fertilisation position, mm; c is the number of accurate fault alarms, t is the fault alarm response time, s; and d is the number of tests.

The SPSS 22 (IBM, Armonk, NY, USA) software was used to statistically analyse the fertilisation position error, fertilisation quantity error, and fault alarm times, and to calculate the fertilisation position accuracy, fertilisation quantity control accuracy, and fault alarm

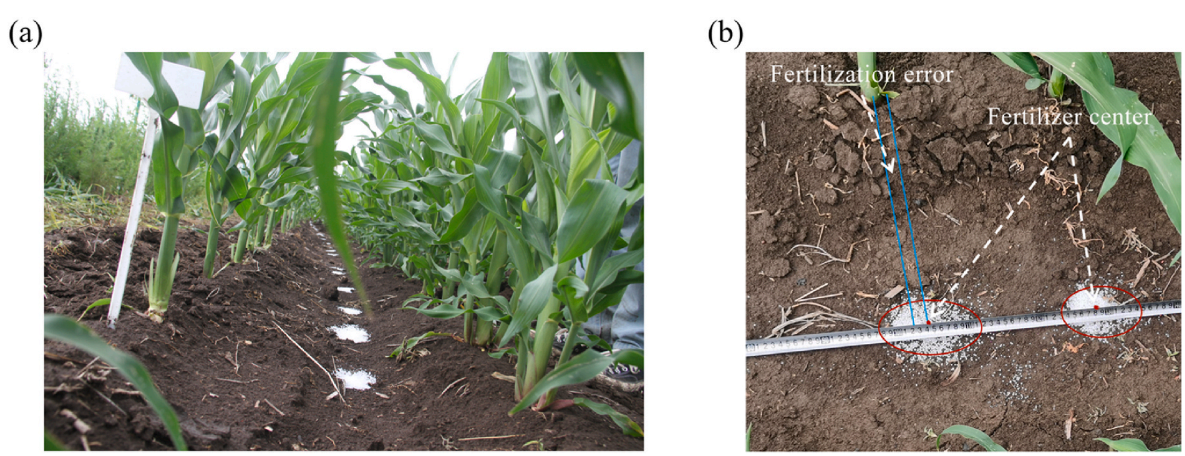

Fig. 12. Field test for targeted fertilisation positioning accuracy: (a) Overall effect of fertilisation; (b) Photograph of the measurement process for fertilisation position error.

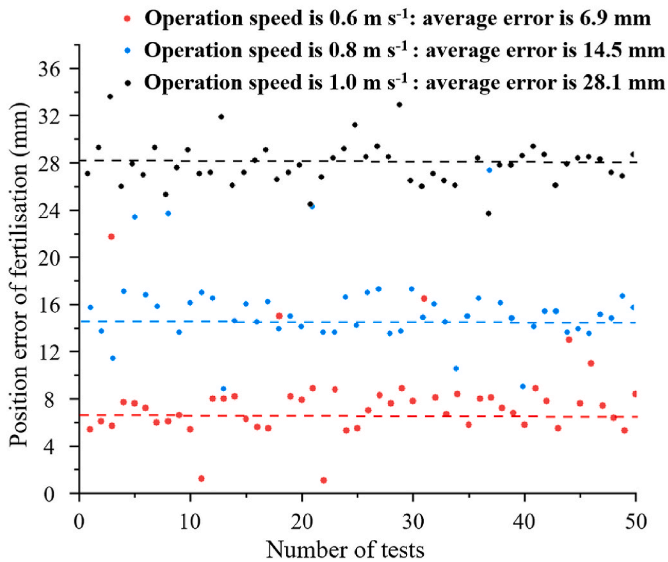

Fig. 13. Scatter plot of targeted fertilisation position under different operation speeds.

Table 1
Statistical results of fertilisation position errors under different operating speeds.

Operating speed (m s^{-1})	Average error (mm)	Maximum error (mm)
0.6	6.9	16.5
0.8	14.5	27.5
1.0	28.1	33.7

accuracy. Origin 2021 (OriginLab, Hampton, MA, USA) software was used to visualise the targeted fertilisation test data.

3. Results and discussions

3.1. Analysis of targeted fertilisation position accuracy test results

The fertilisation position accuracy is an important indicator of the performance of targeted fertilisation operations. The intelligent targeted fertilisation system designed in this study was validated for fertilisation position accuracy using targeted fertilisation bench tests. The target fertilisation point was set as the row-side position corresponding to each maize plant (Fig. 9a). After the fertilisation operations were completed, the distance between the centre point of fertilisation of a single plant and the target fertilisation point was measured and recorded as the fertilisation position error (N_l) (Fig. 9b). Initially, when the fertilisation operation speed was 0.6 m s^{-1}, most of the maize plant fertilisation position errors were in the range of 0.0–15 mm. As the fertilisation operation speed increased to 1.0 m s^{-1}, the fertilisation position error increased, with most errors concentrated in the range of 20–35 mm (Fig. 10). Furthermore, with an increase in the target fertilisation quantity, the fluctuation in position error was relatively small, with an average increase of only 1.6 mm. At 0.6 m s^{-1}, the average fertilisation position error was less than 6 mm, and at 1.0 m s^{-1}, it was less than 26.5 mm (Fig. 11). Across the three tested speeds, the average fertilisation position error was less than 20 mm, which was not significantly different from the relative distance from the maize roots.

In summary, the bench tests demonstrated that increasing the target fertilisation quantity caused only minor fluctuations in position error, whereas increasing the operating speed resulted in a clear upward trend. Even at the maximum speed, the mean error remained below 26.5 mm. Considering that the typical maize plant spacing is 200–300 mm, these deviations are small relative to plant spacing and thus satisfy the agronomic requirements for targeted fertilisation.

Further verification of the fertilisation position accuracy was conducted through field experiments (Fig. 12), with the overall fertilisation effect and the measurement process of fertilisation position error shown in Fig. 12a and b, respectively. At an application rate of 5.3 g $plant^{-1}$, tests were performed at operation speeds of 0.6, 0.8, and 1.0 m s^{-1}. The distribution of position errors is shown in Fig. 13, with the corresponding statistics in Table 1. The mean error increased with speed, rising from 6.9 mm at 0.6 m s^{-1} to 28.1 mm at 1.0 m s^{-1}. At 0.6 and 0.8 m s^{-1}, several larger deviations occurred, possibly due to transient granule bridging at the fertiliser outlet, stick–slip behaviour of the drive at low speeds, or encoder resolution limits when angular increments were small. At 1.0 m s^{-1}, the fertiliser flow was more continuous and drive inertia may have reduced stick–slip, leading to a tighter distribution. The larger mean error at 1.0 m s^{-1} can be explained by the fixed system response time, which translates into greater positional deviation at higher speeds. From an agronomic perspective, even the maximum deviation of 33.7 mm was much smaller than the typical maize plant spacing of 200–300 mm, and was therefore acceptable for field application.

3.2. Analysis of targeted fertilisation quantity control precision test results

Through targeted fertilisation bench tests, the precision of the fertilisation control of the intelligent targeted fertilisation system designed in this study was validated to meet the requirements of practical fertilisation operations. After the fertilisation operation was completed, the fertiliser in the receiving box on one side of the maize plant was weighed and recorded. The statistical curve of the fertilisation quantity of maize plants and the curve of the fertilisation quantity control precision were plotted. The dispersion of the fertilisation quantity at the three operating speeds was small, and the average absolute error between the actual fertilisation quantity and the target fertilisation quantity was less than 1.0 g, with an average relative error of less than 5.0 % (Fig. 14). First, when the target fertilisation quantity was 5.3 g $plant^{-1}$ and the operation speed was 0.6 m s^{-1}, the average absolute error of the fertilisation quantity was 0.16 g, and the average relative error was 3.02 %. With an increase in the operation speed to 1.0 m s^{-1}, the average absolute and relative errors of the fertilisation quantity increased by 0.24 % and 4.53 %, respectively. An increase in operation speed led to an increase in the fertilisation position error, with certain fertilisation quantities remaining at the target fertilisation position. Second, the fertilisation quantity control precision (N_b) at different operating speeds was greater than 95 % (Fig. 15). With an increase in operation speed, the fertilisation quantity control precision showed a significant downward trend. Because the BPNN controller in the intelligent targeted fertilisation system can adaptively learn and adjust the parameters of the PID control to continuously optimise the angular displacement of the fertilisation motor, multiple local minimum points appeared irregularly in the fertilisation quantity control curve of each group of tests because of insufficient learning of the parameters at the initial stage of each experiment (Fig. 15). Finally, when the operation speed was 0.8 m s^{-1} and the target fertilisation quantity was 5.3 g $plant^{-1}$, the average absolute error of the fertilisation quantity was 0.21 g, and the average relative error was 3.96 %. With an increase in the target fertilisation quantity to 15.9 g $plant^{-1}$, the average relative error of the fertilisation quantity increased to 4.09 % with minimal variation.

3.3. Reliability analysis of targeted fertilisation fault monitoring

Insufficient fertiliser, blockage of fertiliser pipes, and abnormal operation speeds may affect the efficiency of targeted fertilisation operations. The reliability of the monitoring system was verified through fault-simulation tests. As shown in Table 2, each type of fault was tested 100 times, and the alarm accuracy rates (N_c) for pipe blockage, insufficient fertiliser, and abnormal operating speeds were all above 97 %.

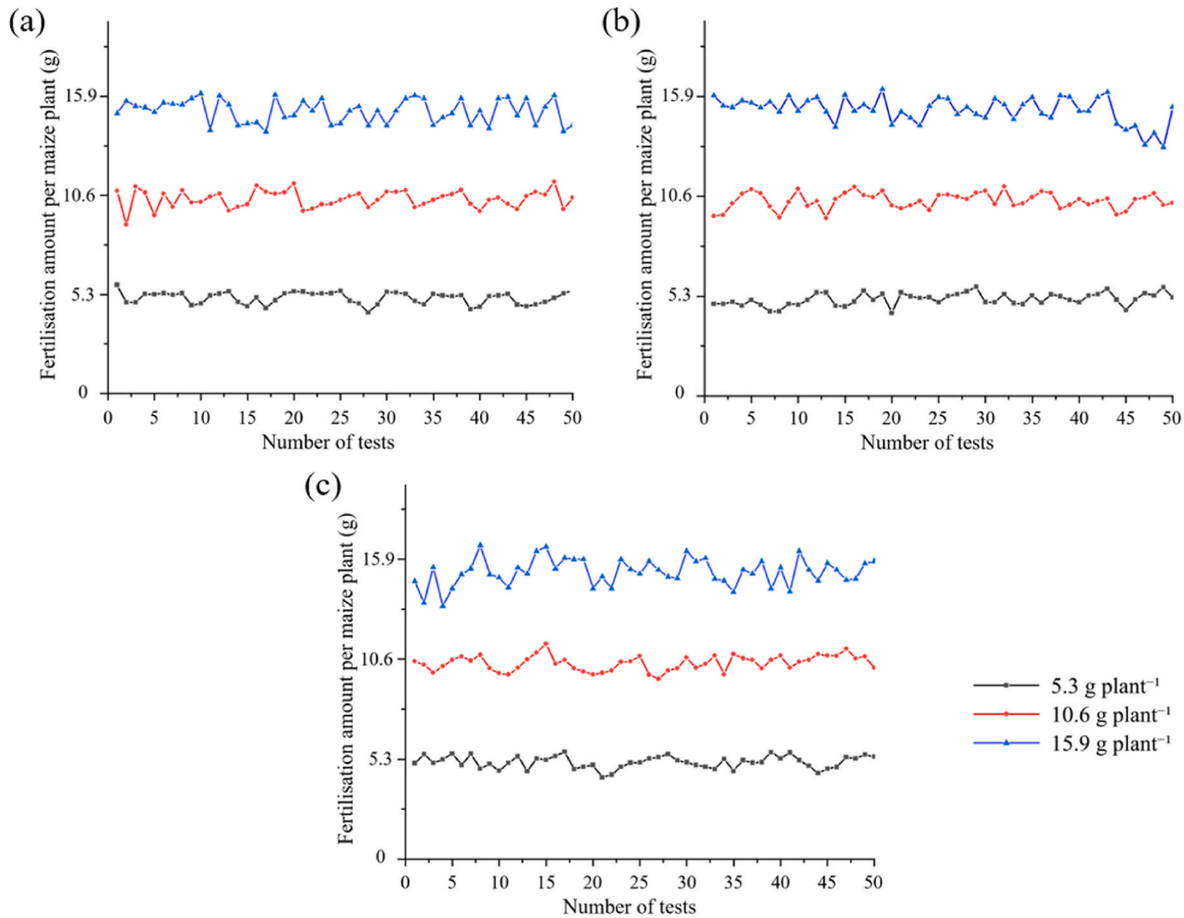

Fig. 14. Line graph of fertilisation amount error of maize plants: (a) Operation speed is 0.6 m s^{-1}; (b) Operation speed is 0.8 m s^{-1}; (c) Operation speed is 1.0 m s^{-1}.

The average response time of the alarms was less than 0.45 s, indicating stable and rapid system feedback. Although occasional false or missed alarms occurred, the system re-evaluates each fertilisation event independently, so errors are unlikely to persist to subsequent plants. Overall, the monitoring system met the reliability requirements of practical targeted fertilisation operations.

4. Discussion

The performance of the intelligent maize-targeted fertilisation system was comprehensively validated through bench and field experiments. The results indicated that operating speed, target fertilisation amount, and fault monitoring all exerted significant effects on fertilisation quality. Overall, the proposed BPNN–PID adaptive control approach achieved stable performance in terms of fertilisation quantity accuracy, fertilisation position accuracy, and fault detection capability, thereby confirming its engineering feasibility and agronomic applicability.

Firstly, regarding fertilisation position accuracy, the experiments showed that operating speed had a far greater impact than target fertilisation amount. As speed increased from 0.6 m s^{-1} to 1.0 m s^{-1}, the position error increased substantially, whereas variations in target fertilisation amount (5.3–15.9 g plant^{-1}) caused only minor fluctuations. This phenomenon was mainly due to the fixed detection–execution response delay in the system, which translates into a larger positional deviation at higher speeds. At lower speeds (0.6 and 0.8 m s^{-1}), occasional large deviations were observed, which were more likely caused by transient granule bridging at the fertiliser outlet, intermittent stick–slip behaviour of the drive system, or encoder resolution limitations under small angular increments. At 1.0 m s^{-1}, the fertiliser flow was more continuous, and drive inertia reduced stick–slip, leading to a more concentrated error distribution. Nevertheless, the maximum deviation of 33.7 mm remained much smaller than the typical maize plant spacing of 200–300 mm, thereby confirming the agronomic acceptability of the system under field conditions.

Secondly, with respect to fertilisation quantity control accuracy, the BPNN PID controller exhibited superior dynamic performance compared with conventional PID control. The BPNN–PID controller achieved a settling time of 0.9 s, 0.6 s shorter than the traditional PID, while completely eliminating overshoot. The fertilisation quantity control accuracy reached 96.98 %. This improvement stemmed from the self-learning and adaptive adjustment capabilities of the neural network, which enabled dynamic tuning of PID parameters according to real-time deviations. Across different target fertilisation amounts, the error remained at a low level, demonstrating stable control under varied conditions.

Thirdly, in terms of fault monitoring performance, the integrated multi-sensor monitoring module successfully identified and alarmed common failures, including fertiliser tube blockage, missing fertiliser in the box, and abnormal operating speed. Experimental results indicated short response times and high alarm accuracy, with rates exceeding 97 %. This capability ensured stable system operation, reduced the risk of application failure due to blockage or missed fertilisation, and improved the reliability of the equipment. Compared with traditional reliance on manual inspection, the automated monitoring and alarm functions significantly enhanced operational safety and efficiency, thereby strengthening the practical value of the system.

Further comparison with previous studies highlights the advancements achieved in this work. As shown in Table 3, the average fertilisation position error of this system ranged from 6.9 to 28.1 mm across

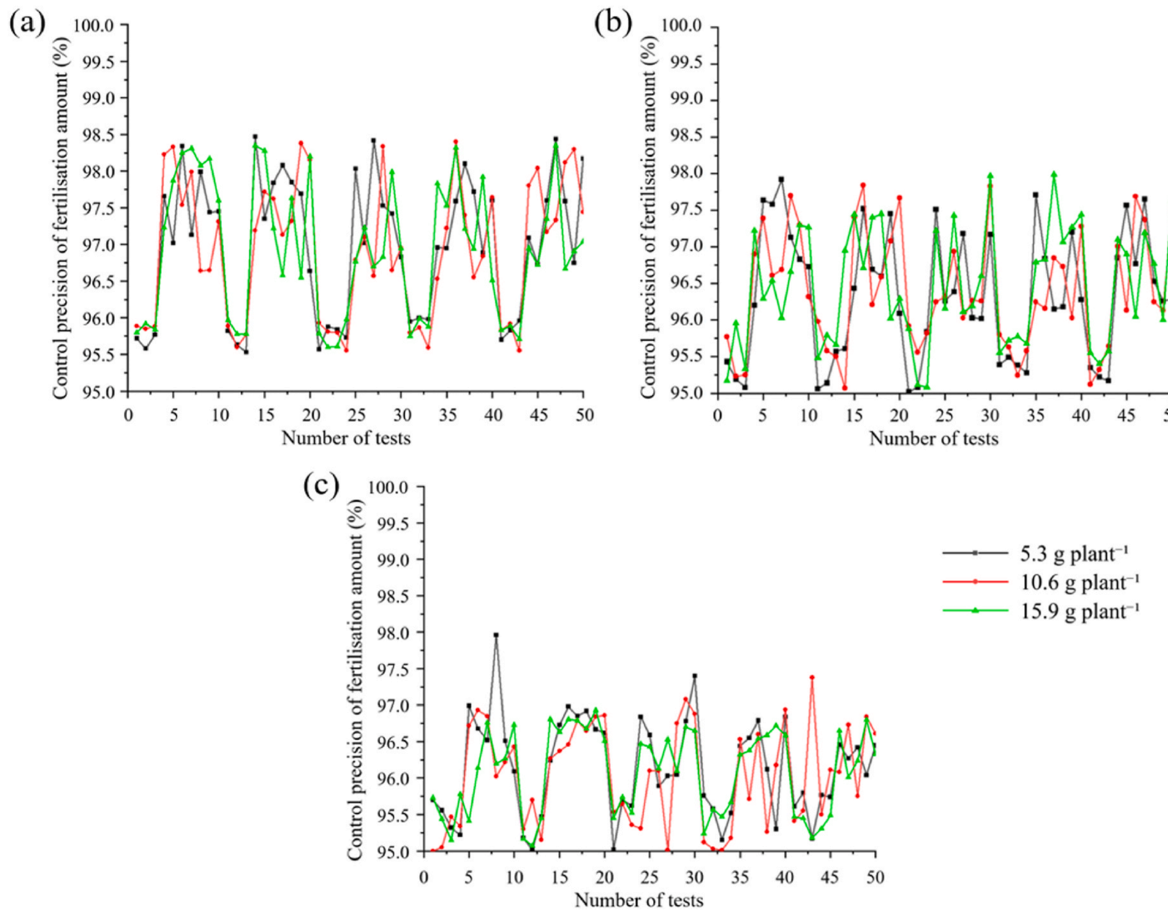

Fig. 15. Line graph of fertilisation application control accuracy for maize plants: (a) Operation speed is 0.6 m s^{-1}; (b) Operation speed is 0.8 m s^{-1}; (c) Operation speed is 1.0 m s^{-1}.

Table 2
Results of fault alarm function testing.

Fault type	Test number	Alarm number	Number of false alarms	Number of missed alarms	Average response time (s)	Alarm accuracy rate (%)
Blockage of fertiliser pipes	100	98	1	1	0.4	98
Insufficient fertiliser	100	100	0	0	0.41	100
Abnormal operation speeds	100	97	1	2	0.45	97

Table 3
Comparison of fertilisation position errors in previous studies and this study.

Study/ Method	Detection & Control Method	Average fertilisation position error (mm)	Main limitations
Zong and Liu (2021)	Machine vision detection + actuator control	32	Long processing delay, fertilisation lag
Yang et al. (2017)	Photoelectric dual-model detection + sequential signal processing	41	Sequential detection and actuation caused significant delay
This study	Dual-sensor detection + BPNN–PID adaptive control	6.9–28.1 (depending on speed)	Fixed sensing/ actuation delay, occasional false detections in field

different speeds. By contrast, Zong and Liu (2021) reported an error of 32 mm using a machine-vision-based approach, while Yang et al. (2017) observed 41 mm with a photoelectric dual-model method. By integrating dual-sensor detection with adaptive neural-network control, the present system effectively reduced positional errors and demonstrated a marked improvement. Similarly, Table 4 shows that the BPNN PID controller outperformed the conventional PID controller (He et al., 2017) in terms of system dynamics: the settling time was reduced from 1.5 s to 0.9 s, overshoot was eliminated, and fertilisation quantity control accuracy reached 96.98 %. These findings confirm that

Table 4
Comparison of conventional PID and BPNN–PID controllers.

Controller type	Settling time (s)	Overshoot	Application-rate accuracy (%)	Notes
Conventional PID (He et al., 2017)	1.5	Present	–	Longer response time, overshoot present
BPNN–PID (This study)	0.9	None	96.98	Faster convergence, stable response, adaptive tuning

neural-network-assisted parameter tuning can significantly enhance the responsiveness and stability of fertilisation systems, providing a feasible pathway for the development of precision agricultural equipment.

Despite these advances, certain limitations remain under field conditions. Environmental variability, uneven soil and terrain, and occasional sensor errors can still influence fertilisation precision. The current BPNN PID control framework is not yet sufficient to fully compensate for these uncertainties. Future work should therefore focus on: (i) strengthening multi-sensor fusion to improve robustness in crop detection and operation monitoring; (ii) optimising the fertiliser outlet design to minimise transient bridging or particle blockage; and (iii) incorporating speed closed-loop feedback in addition to position feedback, thereby enabling dual closed-loop control to enhance system stability under complex conditions (Le et al., 2017; Bernardi et al., 2022).

In summary, this study not only validated the performance of the intelligent maize-targeted fertilisation system under experimental conditions but also provided important engineering insights for the design of agricultural equipment. The results highlighted that fixed system response delays at higher speeds were the key factor limiting position accuracy, offering direction for future optimisation of real-time control algorithms and actuator design. From an agronomic perspective, the observed deviations were far smaller than maize plant spacing, ensuring that crop growth would not be adversely affected. Therefore, the proposed approach provides both engineering guidance for improving real-time control precision and scientific evidence supporting the broader application of targeted fertilisation technology in precision agriculture.

5. Conclusion

This study proposed and validated an intelligent maize-targeted fertilisation system based on a BPNN PID adaptive feedback control strategy. By integrating dual-sensor detection, adaptive parameter tuning, and multi-sensor fault monitoring, the system achieved stable fertilisation quantity control, reliable positioning accuracy, and timely fault detection under both bench and field conditions. These findings confirm that the approach can effectively address the typical limitations of traditional fertilisation systems, such as unstable positioning accuracy and delayed response. From both engineering and agronomic perspectives, the proposed method provides a feasible and practical solution for enhancing the responsiveness, stability, and reliability of fertilisation equipment. Overall, the work offers valuable guidance for the design of next-generation intelligent fertilisation machinery and contributes to advancing precision and sustainable agriculture.

CRediT authorship contribution statement

Wenqi Zhou: Validation, Supervision, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Huaiyu Liu:** Software, Validation, Writing – review & editing. **Yao Wang:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Writing – original draft, Writing – review & editing. **Cunliang Liu:** Validation, Project administration, Methodology, Data curation, Conceptualization. **Han Tang:** Supervision, Resources. **Qi Wang:** Supervision, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Jinwu Wang:** Validation, Methodology, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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