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Research Progress on Closed-Loop Control Technology for Key Operation Stages of Combine Harvesters

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Abstract. During the operation of a combine harvester, the crop state changes continuously and the load disturbances are obvious, while low loss, high efficiency and stability constrain each other, so it is difficult to take all of them into account by relying only on fixed parameters or single-variable open-loop regulation. This paper summarizes the perception, decision and execution mechanisms according to four types of stages, namely forward speed and feed rate, threshing and separation, cleaning, and header profiling, and compares the progress of machine learning, fuzzy control, model predictive control, multi-sensor fusion and soft measurement according to the completeness of the closed loop and the level of validation. Research is moving from single-parameter feedback toward multi-source perception, feedforward-feedback fusion and multi-variable coordinated optimization, but online quality perception, cross-crop generalization, subsystem coupling, real-time deployment and long-term field validation remain weak. Follow-up work should strengthen model-data fusion estimation, hierarchical multi-objective control, lightweight deployment, actuator dynamic compensation and safety fault tolerance, so as to improve the autonomous operation capability in complex field environments.

Keywords: combine harvester, closed-loop control, adaptive regulation, multi-sensor fusion, model predictive control, intelligent harvesting

1. Introduction

The forward feeding, threshing and separation, cleaning and header operations of a grain combine harvester are interrelated, and the grain loss rate, breakage rate, impurity content, operating efficiency and energy consumption are all jointly determined by them. Crop density, moisture content, straw–grain ratio, lodging condition and terrain fluctuate with time and space, and the material flow and mechanical load rise and fall accordingly. Relying only on driver experience to set fixed parameters or carry out open-loop regulation often fails to respond in time, and problems such as overload blockage, incomplete threshing, increased breakage, increased cleaning loss and profiling lag are prone to occur. Therefore, closed-loop control based on real-time perception, state estimation and execution regulation is an important foundation for low loss, high efficiency, stability and even autonomous operation [1].

Existing reviews have focused on process monitoring and control sensors and systematically summarized the state perception of combine harvesters and its applications [1], but how each stage

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moves from perception to decision, execution and quality feedback lacks a unified closed-loop chain comparison; there is also no consistent maturity judgment among state perception, parameter recommendation, control simulation, bench closed-loop and field closed-loop. The coupling effect of material flow and power flow between subsystems still needs to be summarized within the whole-machine control framework.

This paper is developed around four types of stages, namely forward speed and feed rate, threshing and separation, cleaning, and header height and profiling; it sorts out the control mechanisms and recent progress, compares perception methods, control methods, closed-loop completeness and validation levels, and discusses issues such as state perception, model generalization, system coupling, execution constraints and engineering verification, providing a reference for whole-machine coordinated control and unmanned operation.

Literature scope and classification method: the literature cited in this paper covers 2017–2026, of which 42 papers were published in 2021–2026. The full text is organized by four types of operation stages, and distinguishes state perception/prediction, parameter recommendation, control simulation, bench or prototype closed-loop, and field closed-loop. Any detection, identification or prediction work that does not drive an actuator or form real-time feedback is regarded only as perception or decision support and is not listed as a complete closed loop.

2. Overall architecture and technical connotation of closed-loop control for combine harvesters

The closed-loop control of combine harvesters takes operating quality and machine load as the main line, forming a dynamic cycle of "state perception–state estimation and decision–execution regulation–effect feedback". The system takes the target feed rate, allowable load, grain loss, impurity content and header height as the basis, combines the machine and crop states to calculate commands such as forward speed, drum speed, concave clearance, fan speed, sieve opening and header position, and then continuously corrects them according to the state and quality feedback after execution. If information can be obtained before crop or terrain disturbances enter the controlled object, feedforward can also be introduced to weaken the influence of time delay.

From a system perspective, a combine harvester is a time-varying coupled object with multiple inputs and multiple outputs: the forward speed changes the feed rate and the threshing and cleaning loads; the drum speed and concave clearance affect the degree of threshing, breakage rate, power consumption and the material composition entering the cleaning system; the fan speed and sieve opening jointly determine the cleaning loss and impurity content; the header height, actual cutting width and body posture change the feeding state from the inlet end. The various stages are connected as a whole through material flow, power flow and information flow, and local adjustments often affect subsequent quality indicators, so control must coordinate all manipulated variables and seek optimization among operating quality, efficiency, energy consumption, blockage risk and execution constraints.

The system can be divided into four layers: perception, state estimation and decision, execution, and feedback evaluation. The perception layer collects information such as feed rate, rotating speed, torque, pressure, vibration, moisture content, loss and terrain, and then completes filtering, feature extraction, soft measurement and working condition identification; the execution layer adjusts parameters by means of hydrostatic travel, electro-hydraulic proportional valves, motors or servo mechanisms, and finally evaluates the load and operating quality. What needs to be explained is that machine learning prediction or parameter recommendation constitutes an online closed loop only when connected to execution and forming real-time feedback [1]. The evaluation should also take

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into account field disturbances, as well as the real-time performance, robustness and transferability across crops and working conditions.

Table 1. Closed-loop control variables and objectives of key operation stages of combine harvesters

Operation stage	Main manipulated variables	Main feedback/state variables	Typical external disturbances	Main control objectives
Forward speed–feed rate	forward speed, travel pump/valve opening	feed rate, engine load, drum load	crop density, cutting width, moisture content, lodging	match the processing capacity and avoid overload and blockage
Threshing and separation	drum speed, concave clearance, guide parameters	entrainment loss, unthreshed rate, breakage rate, drum load	feed rate, moisture content, straw–grain ratio	balance complete threshing, low breakage, low loss and low power consumption
Cleaning	fan speed, sieve opening, air guide parameters	cleaning loss, impurity content, screen surface load	composition of threshed products, feed fluctuation	coordinate the loss rate and impurity content
header profiling	header height, lateral inclination, hydraulic valve opening	ground distance, header displacement, body posture	terrain undulation, crop occlusion, vehicle posture	maintain the target stubble height and suppress the risk of ground contact

3. Closed-loop regulation mechanism of key operation stages

3.1. Closed-loop control of forward speed and feed rate

Feed rate refers to the total mass of crop entering the machine per unit time. When the cutting width and crop conditions are fixed, the faster the forward speed, the greater the feed rate; too fast easily causes conveyor blockage, drum overload, incomplete threshing and cleaning loss, while too slow limits the processing capacity and operating efficiency, so speed regulation should match the feed rate with the processing capacity of the machine [2, 3].

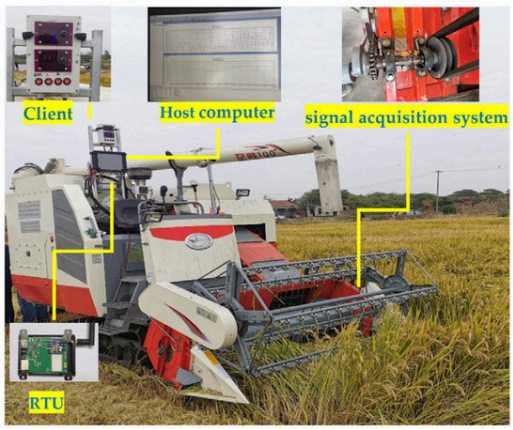


Figure 1. Feed rate monitoring system and field test platform [4]

Grain, ears, stems and leaves are mixed together and difficult to weigh continuously; the feed rate is usually estimated indirectly on the basis of the reel force, the header auger or conveyor and drum torque, conveyor chain tension, hydraulic pressure, engine load and vibration, and can also be predicted in combination with speed, actual cutting width, header height and the crop density ahead.

The controller compares the measured feed rate or load with the target value: when the feed rate is excessive or approaches the load limit, it decelerates through the displacement of the hydrostatic

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pump, the opening of the proportional valve or the rotating speed of the travel motor; when the feed rate is insufficient and the processing capacity has surplus, it accelerates, and continuously corrects with speed, feed rate and load feedback. Combined with front-end crop density or reel force prediction, a "feedforward prediction + in-machine load feedback" approach can be formed to reduce the lag of speed regulation.

3.2. Closed-loop control of threshing and separation

The threshing device relies on the striking, rubbing and squeezing between the drum or rotor and the concave to make grain fall from the ears; the separation device then separates the threshed grain from the straw and other threshed products. The feed rate, crop moisture content, drum speed, concave clearance, guide plate angle and material residence time all affect the quality of threshing and separation [5].

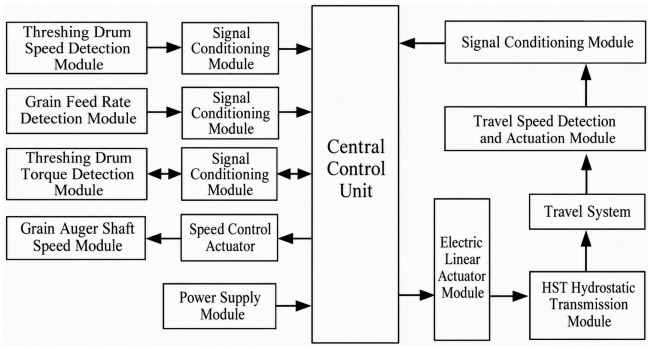


Figure 2. Schematic diagram of the closed-loop control system structure for threshing and separation [6]

The difficulty of threshing control lies in balancing the unthreshed rate, breakage rate, entrainment loss, load and power consumption. If the rotating speed is too low or the clearance is too large, threshing is often incomplete and the entrainment loss increases; conversely, the impact and squeezing are intensified, which is favorable for threshing but may increase breakage, power consumption and blockage risk [7].

In the system, a rotating speed sensor measures the drum speed, the load is reflected by torque, hydraulic pressure or current, the concave clearance is detected by displacement or angle, and a piezoelectric impact sensor is also installed at the end of the separation section to capture grain discharged along with the straw. When conditions permit, the unthreshed rate and breakage rate can be estimated by means of vision, acoustics or spectroscopy.

The piezoelectric element converts the vibration generated by grain impacting the sensitive plate into an electrical signal, and then distinguishes grain impacts from straw and chaff impacts according to amplitude, frequency, duration and waveform, estimating the separation loss per unit time.

The direction of regulation should take into account the working conditions and quality constraints: when the load and breakage rate are within limits but the entrainment loss increases, the rotating speed can be increased, the clearance reduced or the guide components adjusted; when breakage, power consumption or load is high, the rotating speed should be reduced or the clearance increased. Since the crop, moisture content, feed rate and drum structure can change the action rules of the parameters, constrained multi-objective decision-making should be adopted to avoid the rigid application of fixed rules.

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The concave clearance can be adjusted by an electric push rod, servo motor, hydraulic cylinder or crank-link mechanism, and can also be continuously adjusted by changing the drum diameter hydraulically. After the action, the clearance is detected by displacement, and the effect is evaluated by loss and load feedback.

3.3. Closed-loop control of cleaning

The cleaning system uses the airflow generated by the fan and the reciprocating motion of the vibrating screen to separate grain from chaff, short straw, broken leaves and other impurities. The main control parameters are fan speed, sieve opening, air guide plate angle, and vibrating screen frequency and amplitude, and the main evaluation indicators are the cleaning loss rate, grain tank impurity content and cleaning processing capacity.

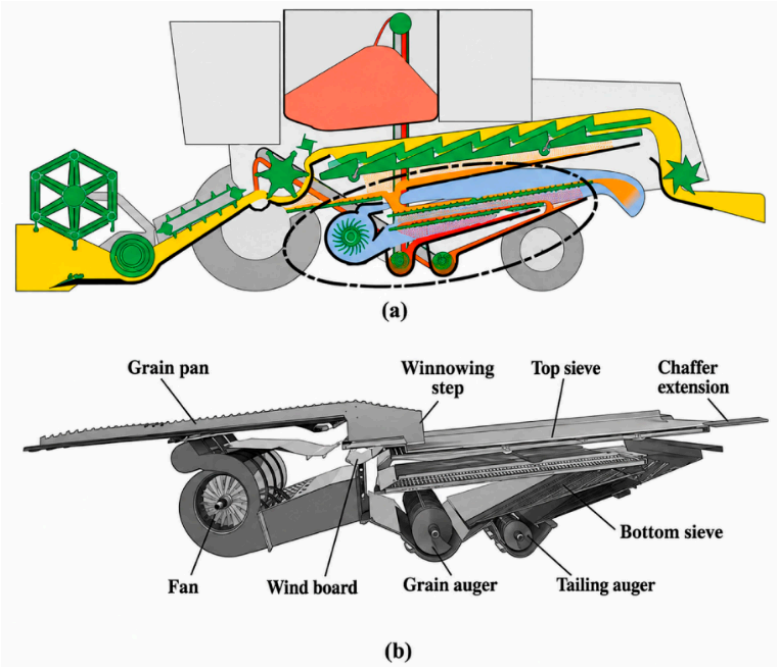


Figure 3. Schematic diagram of the cleaning system structure of a combine harvester [8]

If the fan speed is too low, the impurity content tends to increase; if it is too high, grain is easily blown out. If the sieve opening is too small, it limits the passing capacity and causes accumulation and blockage; if it is too large, it increases the impurities entering the grain tank. It can be seen that the fan and sieve parameters need to be coordinated, and the loss and impurity content must be weighed together.

The cleaning closed loop detects loss with a piezoelectric sensor at the screen tail, measures fan speed with a Hall sensor or encoder, and measures the positions of the sieve and air guide plate with angle or displacement sensors; the screen surface load can be estimated through wind speed, differential pressure, vibration and capacitance. The impurity content is difficult to measure directly and continuously, and is often calculated by means of vision or soft measurement based on the fan, sieve and feed rate, thereby forming multi-objective control that combines direct feedback with quality soft measurement.

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3.4. Header height and profiling control

The header height determines the stubble and the composition of the fed material: too high may cause missed cutting of low-position ears, while too low increases the stem load and causes soil scooping or ground contact. Profiling control needs to adjust with the terrain so that the cutter keeps the set height relative to the ground or the canopy [9].

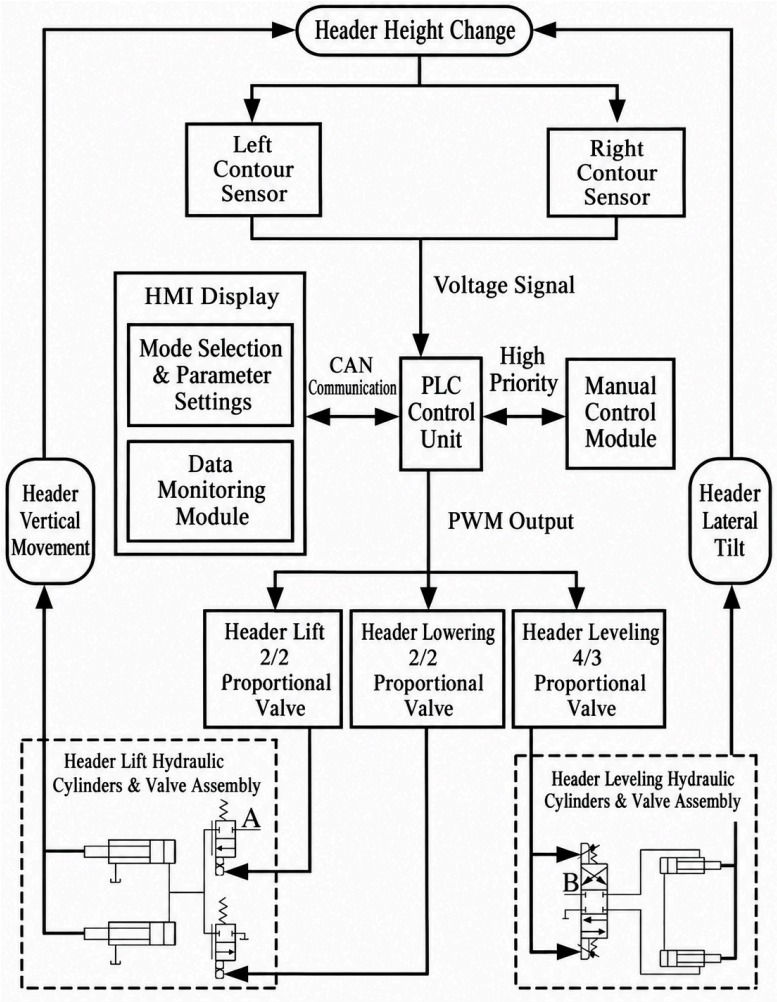


Figure 4. Cooperative profiling system for header longitudinal height and transverse inclination [10]

Contact detection uses ground wheels, sliders or mechanical feelers to follow the ground, and then converts the displacement with angle sensors or potentiometers; it has a simple structure but is easily affected by soil clods, entanglement and obstacle impacts [11]. Ultrasonic, vision and LiDAR detection can achieve forward-looking detection, reserving time for hydraulic action; area array radar provides multi-point distances to reconstruct the terrain, but non-contact detection is affected by occlusion, dust and surface reflection.

The actual position of the header is obtained from hydraulic cylinder displacement, draw-wire displacement or linkage angle sensors, and pitch and roll are compensated by an inertial measurement unit. A wide header coordinates lifting and lateral inclination by combining the left and right profiling signals [12]; the controller drives the proportional valve and hydraulic cylinder according to the height error and corrects it with position feedback. High-speed operation also needs

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to combine forward-looking detection, attitude and actuator dynamic compensation to deal with the lag caused by valve dead zone, oil compressibility, inertia and load changes.

4. Recent progress and comparison of closed-loop control research

4.1. Research on feed rate perception and forward speed closed-loop control

Feed rate monitoring is moving from indirect measurement of in-machine load to front-end force measurement and multi-source fusion. Zhang et al. used multi-sensor decision-level fusion to improve the accuracy and stability of throughput monitoring [13]; Sun et al. combined feed monitoring with yield spatial distribution estimation [14]; Chen et al. established an online field operating performance evaluation system [15], promoting the joint perception of material flow and whole-machine performance.

In 2025, Chen et al. designed a feed rate monitoring system based on the reel force, consisting of a plant bending force detection device, a header height angle sensor, GNSS, a microprocessor and a display terminal; they used plant bending force, forward speed, reel rotating speed and header height as model inputs and an optimized neural network to calculate the instantaneous feed rate. In field experiments, the model achieved a coefficient of determination of 0.931, a mean absolute percentage error of 1.21% and a root mean square error of 0.03 kg/s, and could perceive the feeding state before the crop entered the inclined conveyor, providing a high-precision input signal for forward speed feedforward control [16].

In 2025, Zhang et al. developed a fault prediction and speed control system for unmanned combine harvesters, installing Hall speed sensors on key components such as the header auger, inclined conveyor, threshing drum, fan, vibrating screen, grain auger and straw chopper, judging blockage risk according to the rotating speed and slip rate, and classifying faults with a support vector machine optimized by an improved particle swarm algorithm. On 1071 groups of valid data, the overall recognition accuracy of the model for the normal, slight blockage, severe blockage and complete blockage states reached 98.59%. The system inputs the blockage risk and feed rate estimation results into a fuzzy controller and adjusts the hydrostatic travel system through an electric actuator; in field experiments, after slight blockage was detected, the system could automatically reduce speed within 0.5–2 s, and complete blockage was avoided in multiple tests.

The speed regulation target has expanded from a constant feed rate to the coordination of efficiency, blockage and overload. However, the model still needs to be calibrated according to variety, moisture content, density and header height, and may become inaccurate across regions and machine models; Zhang et al. collected data only on a single machine model and a single field, so the generalization ability remains to be verified with expanded samples [17].

In addition, Zhang et al. used improved YOLOv5s to identify wheat and combined it with single-plant mass to predict the feed rate [18]; Sun et al. used multi-source information and data amplification to predict and control the speed of unmanned rice harvesters [19]; Wang et al. used multi-sensor fusion [20] and multimodal data-driven methods [21] respectively to estimate and predict in-machine throughput. The coordination of front-end vision, in-machine fusion and speed control can reduce the lag, but signal synchronization, cross-crop transfer, and robustness under occlusion and vibration still need to be solved.

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4.2. Research on closed-loop control of threshing and separation

Based on feed rate monitoring, Fan et al. used an electro-hydraulic mechanism to adjust the concave clearance in real time and verified the comprehensive improvement in efficiency, breakage rate and entrainment loss relative to a fixed clearance [22]. Zhang et al. used temporal proximity soft actor-critic deep reinforcement learning to optimize multiple parameters of maize threshing [23]. The former forms a perception–matching–execution feedback, while the latter expands learning-based decision-making; the optimization effect of reinforcement learning still needs to be evaluated differently from the field execution closed loop, and its maturity depends on online computation, execution constraints and feedback verification.

Fan et al. used experimental data to establish the nonlinear relationship among feed rate, threshing parameters, quality and power consumption, and compared random forest, support vector machine and multiple linear regression, finding that the random forest is more suitable for recommending combinations such as drum speed and concave clearance according to the feed rate. This type of method can handle parameter coupling, but mainly belongs to prediction and optimization decision-making, and is not yet a continuous field quality feedback closed loop [24].

Yang et al. established a dynamic model of threshing and cleaning parameters versus loss rate, impurity content and breakage rate through field identification, coordinated parameter adjustment with model predictive control, and developed a hardware and software system and verified it in Simulink. The results show that it can adapt to coupling and disturbances and is more suitable for handling cross-effects than independent PID, but it depends on model accuracy, and mismatch may occur when the variety, moisture content or straw–grain ratio exceeds the modeling range [25].

Yu et al. developed an automatic control system for the maize threshing concave clearance based on entrainment loss monitoring, using a piezoelectric sensor to detect the entrainment loss and a fuzzy neural network PID algorithm to control the electric adjustment mechanism. In field comparison experiments, after the control system was enabled, the entrainment loss rate was reduced by 43.75%, showing that regulating the concave clearance with operating quality as feedback has an obvious effect [26].

Liu et al. proposed a hydraulic variable-diameter threshing drum control system that continuously adjusts the threshing gap by changing the drum diameter, and carried out research on adaptive state monitoring, providing an execution scheme for adjusting the gap according to the feed rate and drum state [7].

Liu et al. further completed the controller design and field performance verification of the system, connecting state monitoring to the hydraulic execution stage and forming a closed-loop chain of "state monitoring–controller decision–hydraulic execution–field verification" [27].

Liu et al. experimentally verified the feasibility of adaptively adjusting the threshing and separation gap based on feed rate monitoring of the soybean conveying trough [28]; Zhu et al. developed an electric threshing drum and rotating speed control system, enhancing direct execution and dynamic regulation capabilities [29]. Yin et al. constructed a whole-machine digital twin [30], and Guo et al. applied it to threshing performance monitoring [31], providing a virtual-real coordination basis for physical operation, virtual mapping, state diagnosis and parameter optimization.

4.3. Research on closed-loop control of cleaning

Cleaning perception is shifting from grain counting to the identification of impurities and the characterization of the material layer. Li et al. converted vibration–piezoelectric signals into time-

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frequency images and combined them with machine learning to distinguish grain from impurities and assess maize loss [32]; Fu et al. monitored the thickness of the threshed material on the vibrating plate, providing variables for screen surface load estimation [33]; Cui et al. used a band-optimized discrete wavelet transform to improve weak impact identification and loss monitoring under different flow rates and installation conditions [34].

Liu, Wang and Jin used a multi-parameter adjustable device to study the matching relationship between soybean threshed products and the fan and sieve, and carried out adaptive cleaning experiments on the supporting harvester. Online parameter matching can reduce both the loss and the impurity content, showing that the parameters need to be dynamically adjusted with the crop and feeding conditions [35].

In 2026, Pang et al. proposed a fuzzy control system for the operating parameters of the cleaning device, using multi-condition bench data to establish a Gaussian process regression model describing the nonlinear relationship among fan and sieve parameters and the cleaning loss rate and impurity content. Because the impurity content lacks a reliable real-time sensor, the system inputs both the measured loss rate and the model-estimated impurity content into the fuzzy controller, forming a dual-indicator control of "direct sensor feedback + soft measurement model feedback". When the feeding load is disturbed by ±20% and ±35%, simulation and bench experiments show that coordinated parameter adjustment can slow the deterioration of the loss rate or impurity content; however, when the load changes too much or the working condition exceeds the training range, the prediction error may increase, and verification across crops, moisture contents and field conditions is still needed [36].

In terms of loss detection, in 2024 Qu et al. designed a cleaning loss monitoring device suitable for wheat combine harvesters, which identifies grain discharged behind the screen through a bidirectional array piezoelectric sensor and a vibration compensation structure, providing a feedback basis for closed-loop control of the fan and sieve [37]. Shen et al. studied the identification and denoising methods of cleaning loss acoustic signals, attempting to use acoustic features to distinguish grain impacts from other impurities [38]. In 2025, Zhang et al. optimized the structure of the grain loss sensor from the perspective of vibration characteristics, improving the accuracy of real-time detection of the loss rate [39].

Combined with data-driven predictive control [8], cleaning is forming a multi-source perception–quality soft measurement–coordinated control chain. It should be pointed out that loss identification itself is not a complete closed loop; the reliable estimation of loss, impurity content and screen surface load [32-34] must be connected to fan–sieve execution, and the stability and benefits must be verified in continuous field operations; cross-crop calibration, impurity impact interference and mismatch outside the training domain remain to be solved.

4.4. Research on header height and profiling control

Header perception has expanded from ground distance to crop geometry and operating boundaries. Sun et al. used RGB-D to measure the cutting width of rice harvesters, providing inputs for feed rate estimation and speed regulation [40]; Wang et al. used fuzzy decision-making to improve the stability of height measurement [41]; Liang et al. combined deep learning forward-looking vision with dynamic camera attitude correction to jointly estimate rice height and cutting width [42], providing lead time for prediction, attitude compensation and position feedback.

In 2024, Wang et al. developed a header profiling control system for grain combine harvesters, proposed the MSD-MPC algorithm combining multi-sensor data fusion with model predictive control, and designed a single-acting hydraulic cylinder system controlled by a proportional solenoid

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valve. Field experiments showed that within the range of 2–5 km/h, the average coefficient of variation of the header height was 3.5%, the average control accuracy was 91.5%, and there were 0 ground contacts throughout the process; under target heights of 10–25 cm, the average control accuracy was 91.25% [9].

Zhang et al. used an area array LiDAR to collect 8×8 distance points, reconstruct the micro-terrain, distinguish large undulations from negligible fluctuations, and reduce frequent hydraulic actions and local interference. Forward-looking radar can improve the adaptability to complex terrain, but it is affected by dust, occlusion and reflectivity, and should be integrated with feelers, header displacement and body attitude sensors [43].

Xie et al. used multi-feature detection of in-field grain lodging to provide information for adjusting the header and operating parameters in advance according to the lodging direction and state [44]. This study belongs to front-end perception support and should be evaluated separately from the complete execution closed loop.

Overall, header control has shifted from contact-based position feedback to forward-looking prediction and feedback fusion, and the control object has expanded from longitudinal height to height–lateral inclination coordination, with field validation more sufficient than the quality closed loops of threshing and cleaning. For high-speed unmanned operation, it is still necessary to combine terrain/crop prediction, attitude compensation, actuator dynamic compensation and position feedback to deal with unreliable perception, vehicle disturbance, and hydraulic dead zones and time delays.

Table 2. Comparison of closed-loop completeness and validation levels of recent representative studies

Representative study	Control/perception object	Main method	Closed-loop completeness	Validation level	Main limitations/applicable boundaries
Chen et al. [16]	feed rate	reel force + optimized neural network	state perception/prediction	field monitoring	an execution closed loop has not yet been directly formed; cross-crop and cross-machine-model generalization remains to be verified
Zhang et al. [17]	blockage risk and forward speed	IPSO-SVM + fuzzy control	field closed loop	field closed loop	verified on a single machine model and limited fields; long-term continuous working conditions remain insufficient
Fan et al. [24]	multiple threshing parameters	machine learning such as random forest	parameter recommendation	experimental modeling	mainly used for nonlinear parameter mapping; lacks continuous quality feedback
Yang et al. [25]	multiple threshing and cleaning parameters	system identification + MPC	simulation closed loop	control simulation	depends on the accuracy of the dynamic model; insufficient field closed-loop validation
Yu et al. [26]	concave clearance	loss monitoring + fuzzy neural network PID	field closed loop	field closed loop	the coverage of control variables and crop working conditions is still limited
Pang et al. [36]	cleaning parameters	Gaussian process regression + fuzzy control	bench closed loop	simulation + bench	the impurity content relies on soft measurement; lacks long-term field validation

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Table 2. (continued)

Wang et al. [9]	header profiling	multi-sensor fusion + MPC	field closed loop	field closed loop	robustness under complex terrain, dust and hydraulic time delays remains to be verified
Zhang et al. [13]	whole-machine throughput	multi-sensor decision-level fusion	state perception	field monitoring	provides control state variables but has not directly formed a parameter execution closed loop
Sun et al. [19]	operating speed	multi-source information + data amplification + speed control	field closed loop	field closed loop	multi-source synchronization and cross-region/cross-crop generalization remain to be verified
Fan et al. [22]	concave clearance	feed rate monitoring + electro-hydraulic automatic adjustment	experimental closed loop	prototype/experiment	limited dimensions of quality feedback; insufficient validation under complex field disturbances
Zhu et al. [29]	drum speed	electric drum + speed control	actuator closed loop	prototype/experiment	focuses on speed execution control; multi-quality-indicator feedback has not yet been formed
Li et al. [32]	cleaning loss	time-frequency image + piezoelectric signal + machine learning	state perception	experimental identification	solves loss identification; a closed loop with cleaning parameter execution has not yet been formed
Wang et al. [41]	header height	fuzzy decision-making height measurement	state perception	experimental validation	focuses on height measurement; needs further integrated validation with execution control

As Table 2 shows, feed rate prediction, loss identification and crop/terrain perception mostly provide information support, and complete closed-loop achievements are more concentrated in forward speed, concave clearance and header profiling. Model predictive control, machine learning and deep reinforcement learning have enhanced multi-parameter decision-making capabilities, but some achievements are still at the stage of parameter recommendation or simulation, and evaluation needs to take into account algorithm accuracy, closed-loop completeness, validation level and cross-condition generalization ability.

5. Existing problems and future development trends

5.1. Existing problems

(1) Insufficient online perception. Dust, strong vibration, crop impact, illumination and surface reflection reduce sensing stability; feed rate, unthreshed rate, breakage rate and impurity content still lack mature, low-cost and long-term reliable direct measurement schemes, and some controls rely on indirect estimation or soft measurement.

(2) Insufficient generalization and transfer. Most models are established on the basis of limited varieties, moisture contents, feed ranges and a single machine model, and differences in region, crop

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and transmission and threshing structures may cause mismatch outside the training domain, requiring online identification, parameter adaptation and model updating.

(3) Insufficient whole-machine coupling and multi-objective coordination. Local parameter adjustment affects the subsequent load and the composition of threshed products along the material flow and power flow, and may reduce one loss but increase energy consumption or breakage or sacrifice efficiency; actuator dead zones, saturation, time delays and rate limits have also not been fully incorporated into control.

(4) Validation and evaluation are not unified. The working conditions and indicator definitions of offline modeling, Simulink simulation, bench tests and short-term field experiments differ and are difficult to compare directly; unified evaluation is still needed, and validation across crops and regions, long-time continuous operation, and faults and extreme disturbances should be carried out.

(5) The real-time computation and embedded deployment of intelligent algorithms still need to be strengthened. For methods such as YOLO, multimodal fusion, model predictive control, deep reinforcement learning and digital twins, their inference delay, sensor sampling frequency and time synchronization, CAN bandwidth, onboard computing power and model update frequency all affect the control cycle. Once the computational complexity exceeds the response capability of the platform and the actuator, the offline accuracy is difficult to convert into stable field control performance, so the computation time, control cycle and hardware platform should be reported together.

5.2. Future development trends

(1) Development toward multi-source fusion and quality soft measurement. By integrating speed, torque, pressure, vibration, vision, LiDAR and loss signals, crop state, machine load and operating quality can be estimated in a coordinated way; multi-sensor throughput estimation [20], multimodal throughput prediction [21] and forward-looking crop height–cutting width joint estimation [42] have already demonstrated this direction. For impurity content, breakage rate and real-time feed rate, mechanism-constrained soft measurement should be developed, and field robustness should be improved through online correction and uncertainty assessment [1].

(2) Development from fixed models toward model–data fusion and online adaptation. Facing model mismatch under cross-crop, cross-machine-model and cross-region working conditions, the material flow mechanism, dynamic models and machine learning should be combined, and model parameters should be corrected through online identification, transfer learning or incremental updating. The construction of digital twin systems [30] and their application in threshing performance monitoring [31] provide a technical carrier for virtual-real synchronization, state diagnosis and parameter iteration; after forming a two-way data chain with real-time sensing and the controller, they can be used for abnormal state reconstruction and multi-objective parameter optimization.

(3) Development toward hierarchical, multi-variable and multi-objective coordinated optimization. The upper level determines whole-machine objectives by integrating efficiency, loss, impurity content, breakage rate, energy consumption and blockage risk, while the lower level quickly tracks speed, drum speed, concave clearance, fan speed, sieve opening and header posture. Multi-source information speed control [19], feed rate-driven clearance adjustment [22, 28] and electric drum control [29] provide the execution basis; subsequently, model predictive control, constrained optimization and robust/adaptive control should be used to handle variable coupling, execution boundaries and time delays, so as to achieve whole-machine comprehensive optimization.

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(4) Strengthen standardized validation, lightweight real-time deployment and dynamic compensation of execution mechanisms. A hierarchical test system from algorithm simulation to engineering verification should be established by means of hardware-in-the-loop, digital twins and high-coverage field experiments, with unified reporting of the control cycle, computation delay, sampling frequency, hardware platform and the improvement range of quality indicators. Onboard deployment requires model compression, edge inference and time synchronization of multi-source data, and the proportional valve dead zone, hydraulic hysteresis, mechanical clearance and execution rate limits should be explicitly incorporated into the controller, so that "algorithm computability" and "mechanism executability" match on the same time scale.

(5) Integration with fault safety, forward-looking perception, unmanned navigation and task planning. Whole-machine monitoring and fault early warning based on the CAN bus [45] provide safety support for unmanned operation; RGB-D cutting width measurement [40], crop height–cutting width joint estimation [42] and multi-source information speed control [19] make environmental perception a direct input to operating control. In the future, a closed loop of "environment/crop forward-looking perception–load prediction–whole-machine parameter decision–execution control–quality feedback–fail-safe degradation" should be constructed, promoting the development of automatic navigation toward autonomous operation decision-making.

6. Conclusions

(1) From the perspective of technological evolution, the closed-loop control of combine harvesters has gradually developed from fixed parameters and single mechanical signal feedback to multi-source state perception, feedforward–feedback fusion and multi-variable coordinated regulation. Technologies such as forward-looking vision, throughput estimation and soft measurement are introducing crop and environmental information into the control chain in advance, shifting control from after-the-fact load correction to predictive regulation.

(2) From the perspective of technological maturity, the development of the various stages is uneven. Forward speed regulation and header profiling have been verified by more field closed loops, and threshing execution parameters such as concave clearance have also begun to have field regulation capabilities driven by quality or feed rate feedback; in contrast, cleaning and threshing–cleaning multi-variable coordinated control still rely more on soft measurement, parameter recommendation, bench experiments or control simulation, and further engineering is constrained by the online detection of quality indicators such as breakage rate and impurity content and the cross-condition generalization ability of models.

(3) The key in the next stage is no longer just improving the offline accuracy of a single prediction model or sensor, but achieving cross-crop and cross-machine-model generalization, multi-stage coupled coordination, lightweight real-time deployment and reliable long-term field closed loops. For unmanned harvesting, multimodal perception, hierarchical constrained control, actuator dynamic compensation, fault diagnosis and safe degradation should also be unified into the whole-machine closed-loop architecture, forming an autonomous operation capability that is verifiable, transferable and sustainably operable.

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