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Review

Active Disturbance Rejection Control—New Trends in Agricultural Cybernetics in the Future: A Comprehensive Review

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Abstract: With the development of smart and precision agriculture, new challenges have emerged in terms of response speed and adaptability in agricultural equipment control. Active Disturbance Rejection Control (ADRC), an advanced control strategy known for its strong robustness and disturbance rejection capabilities, has demonstrated exceptional performance in various fields, such as aerospace, healthcare, and military applications. Therefore, investigating the application of ADRC in agricultural control systems is of great significance. This review focuses on the fundamental principles of ADRC and its applications in agriculture, exploring its potential use and achievements in precision agriculture management, intelligent agricultural control, and other agricultural control sectors. These include the control of agricultural machinery, field navigation and trajectory tracking, agricultural production processes, as well as fisheries and greenhouse management in various agricultural scenarios. Additionally, this paper summarizes the integration of ADRC with other control technologies (e.g., LADRC, SMC) in agricultural applications and discusses the advantages and limitations of ADRC in the aforementioned areas. Furthermore, the challenges, development trends, and future research directions of ADRC in agricultural applications are examined to provide a reference for its future development.

Keywords: active disturbance rejection control; agricultural automation; precision agriculture; control system integration; agricultural production optimization; system robustness

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1. Introduction

Agriculture, as a fundamental industry responsible for producing food and materials that support human survival and industrial development, is one of the cornerstones of human society. According to a report by the United Nations Food and Agriculture Organization, the global agricultural and food systems produce approximately 9 billion tons of food annually [1], making it a key pillar of many national economies. However, modern agriculture is facing a range of challenges, including environmental changes, resource scarcity, pollution, and low production efficiency.

In response to the intensifying issues of food crises and population aging, countries around the world have initiated the modernization of agriculture [2]. Agriculture 4.0 leverages a range of emerging technologies to upgrade traditional farming methods, optimizing the value chain of global agriculture, while offering disruptive solutions at various stages of the agricultural production chain [3].

With the emergence and development of smart and precision agriculture, agricultural production has become increasingly reliant on unmanned equipment to enhance productivity and efficiency. In the past decade, the use of unmanned intelligent devices, such as Unmanned Ground Vehicles (UGVs), Unmanned Aerial Vehicles (UAVs), Unmanned Surface Vehicles (USVs), and robots in agriculture, has surged dramatically to meet the automation demands of agricultural processes like seeding, crop protection, and harvesting. However, over the past few decades, the complex behaviors and high-precision requirements of unmanned intelligent devices have posed challenges for researchers [4]. Therefore, to meet the needs of smart agriculture, it is essential to develop effective control strategies for unmanned equipment. In recent years, the development and research of effective control for these devices have focused primarily on control strategies such as adaptive control, robust control, and ADRC [5].

In recent years, classical control strategies have been applied to numerous unmanned intelligent agricultural devices [6–18]. Agriculture is a complex system composed of subsystems such as soil, plants, water, climate, and machinery. The nature of biological production in open fields results in unique communication characteristics and control mechanisms influenced by three key factors: climate, soil–water–fertilizer dynamics, and agricultural operations [19]. However, these classical control methods typically consider only simplified mathematical models of agricultural devices. These models (e.g., PID) are often affected by various uncertainties, leading to a decline in control performance [20,21]. It has been demonstrated in many cases that neglecting the effects of uncertainties and disturbances on these models can significantly hinder the achievement of the target motions. Such effects often manifest in the closed-loop stability of unmanned intelligent devices, reducing control precision [5]. Moreover, since agricultural production is a multivariable and complex control process, precision and smart agriculture place higher demands on the control of unmanned devices. The increasing difficulty of designing control systems based on accurate models further limits the development and application of some classical control methods in agriculture.

As a result, the development of advanced control strategies for complex, multivariable, and high-latency control processes in unmanned agricultural devices has become a research hotspot in recent years. In the past few decades, the successful application of ADRC technology in agricultural processes, such as seeding, crop protection, and harvesting, as well as in facility agriculture, has highlighted its vast potential in the agricultural field.

As a model-free control method [22], ADRC has rapidly developed and been successfully applied across various agricultural production domains due to its simplicity of implementation, easy tuning, strong robustness, and high disturbance rejection capabilities [5,20,23]. This control strategy has consistently outperformed traditional methods in experiments across multiple fields. Additionally, similar to PID, ADRC has the ability to self-optimize and integrate with other control methods to achieve coordinated control, and it has been extensively researched and applied in various fields [24,25]. Furthermore,\, numerous researches have demonstrated that combining ADRC with control techniques such as fuzzy control [26,27] and H-infinity robust control [28] yields excellent results. Furthermore, the stability of control can be enhanced by optimizing ADRC parameters through appropriate optimization algorithms [29]. Meanwhile, deep learning has been applied for the real-time tuning of ADRC parameters [30]. The advantages of ADRC, without a doubt, underscore its immense potential for controlling unmanned intelligent devices in various agricultural production processes.

Additionally, other numerical simulations, like molecular dynamics [31–33], have shown their potential for parameter generation as well.

As shown in Figure 1, the research interest in ADRC has been steadily increasing, highlighting its significant potential in the agricultural sector. However, there is currently no review summarizing the applications of ADRC in agriculture. Therefore, the purpose of this paper is to fill this gap by reviewing the current applications of ADRC in agriculture from two perspectives: the traditional ADRC approach and its integration with other technologies. This paper primarily focuses on ADRC control strategies developed within academia and does not include commercial applications of ADRC. Relevant research was identified through searches in databases such as CNKI, PubMed, ScienceDirect, and Web of Science, using keywords such as "ADRC," "Active Disturbance Rejection Control," "Agriculture/Agricultural," and "Crop."

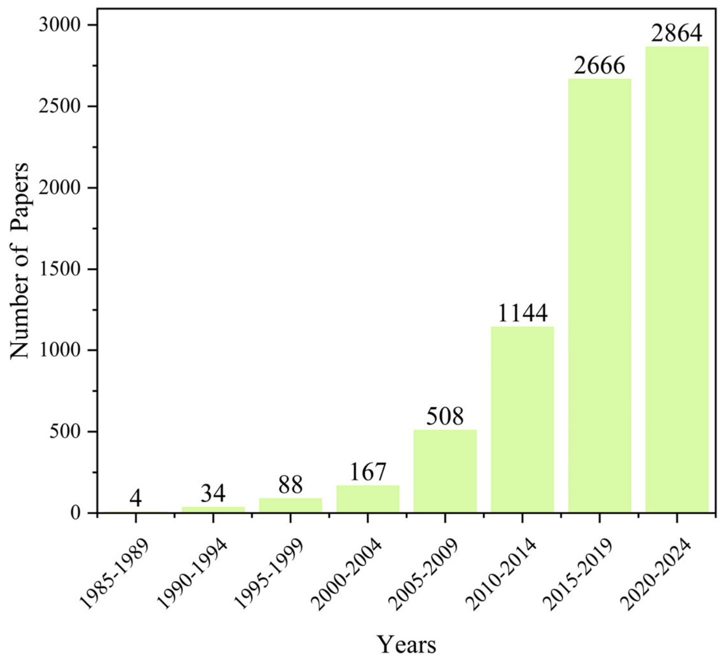


Figure 1. Number of papers accessed on Web of Science using the search terms "ADRC" and "Active Disturbance Rejection Control" every 5 years.

The structure of this paper is as follows as in Figure 2: Section 2 provides an overview of ADRC, briefly reviewing its fundamental components and principles, including the Tracking Differentiator (TD), Extended State Observer (ESO), and Nonlinear State Error Feedback (NLSEF). It also introduces the second-order system as an example to explain these concepts and discusses the current challenges and issues faced by ADRC in agricultural applications; Section 3 presents a detailed review of the current applications of ADRC in agriculture, encompassing the control of agricultural machinery and equipment, field navigation and trajectory tracking, agricultural production processes, and various agricultural scenarios such as aquaculture and greenhouse management; Section 4 reviews the application of optimized ADRC technologies (such as LADRC) and the integration of ADRC with other techniques (such as SMC) in the agricultural field, summarizing the respective advantages of each; Section 5 offers a summary and discussion of the strengths and weaknesses of ADRC in agricultural applications, while also providing some useful suggestions to address the existing shortcomings, offering insights for future research directions; Section 6 concludes with a review and summary of the entire paper.

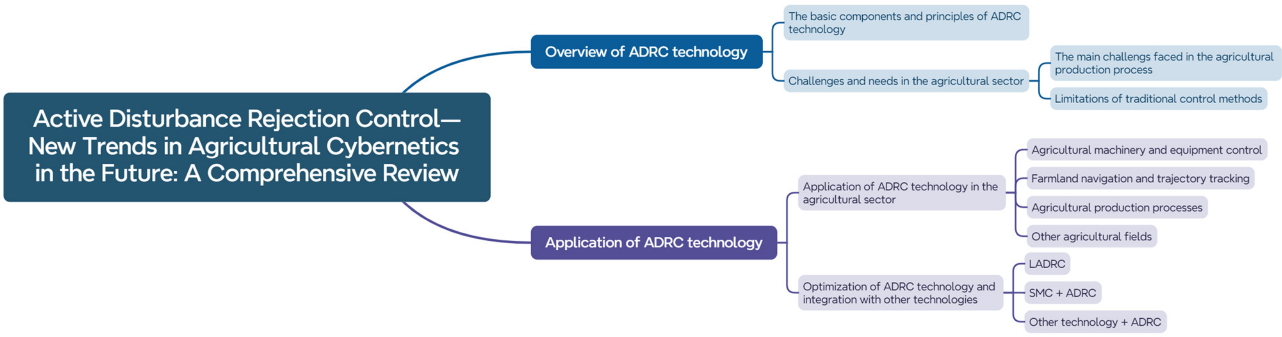


Figure 2. Main categories of applications of ADRC technology in the agricultural field.

This study highlights the integration of Active Disturbance Rejection Control (ADRC) with advanced technologies, emphasizing its effectiveness in enhancing control precision and system robustness within precision agriculture. It underscores ADRC's robustness and adaptability in managing the complex, nonlinear, and uncertain conditions inherent in agricultural systems. While ADRC has rapidly advanced in addressing complex control challenges in precision farming, a comprehensive review remains absent. Future research should focus on field validation, intelligent algorithm optimization, and exploring ADRC's potential to address global agricultural challenges.

2. Overview of ADRC

2.1. Components and Fundamentals of ADRC

Active Disturbance Rejection Control (ADRC) is a novel control theory developed based on PID control principles but independent of the mathematical model of the controlled object. It was first proposed by Han in the 1990s [34–36]. ADRC is primarily used for controlling systems with the following types of uncertainties:

$$x^{(n)} = f(x, \dot{x}, \cdots, x^{(n-1)}, t) + \omega(t) + bu, \tag{1}$$

where f represents the unknown model disturbances and external disturbances. The structure of the ADRC controller is shown in Figure 3, consisting mainly of three parts: (1) the Tracking Differentiator (TD), which arranges the transition process and provides the differential signals of the process; (2) the Extended State Observer (ESO), which observes the internal states of the system; and (3) the Nonlinear Feedback (NF) control scheme, which compensates for system errors [20,37].

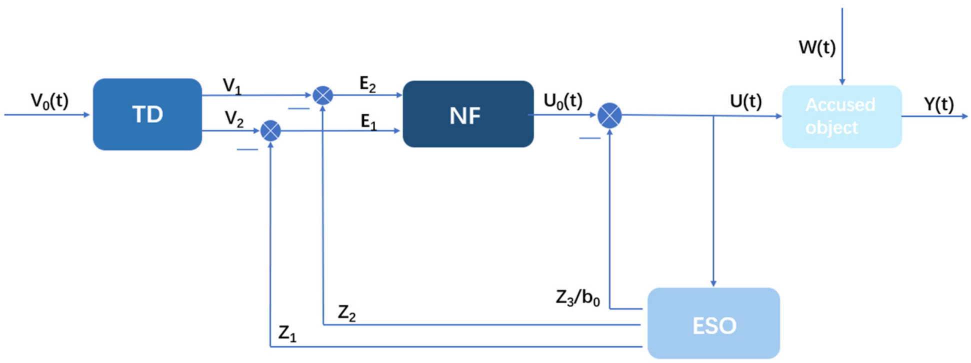


Figure 3. The structure of the ADRC controller.

Equations (2)–(11) briefly explain the three main components of the ADRC controller, using a second-order system as an example. For a second-order system, the controlled object is described as:

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = f\left(x_1, x_2, w, t\right) + bu \\ y = x_1 \end{cases}, \tag{2}$$

where $f\left(x_1, x_2, w, t\right)$ denotes the internal and external disturbances of the system, representing the total disturbance of the system. The stability of ADRC in uncertain second-order systems critically relies on the assumption of boundedness for system uncertainties (f) and their time derivatives ($\dot{f}$). This assumption ensures that the controller can effectively estimate and suppress disturbances without compromising system stability. A 2017 study demonstrated that the boundedness of disturbances and their derivatives is a prerequisite for applying the Lyapunov stability criterion [38]. Based on this, the design of an appropriate Lyapunov function can guarantee system stability under unknown disturbances. Similarly, when disturbances are bounded, the ADRC controller can effectively track reference trajectories and suppress disturbances, thereby ensuring system stability and robustness [39]. Although disturbances in practical applications are not always strictly bounded, ADRC can still perform effective estimation and suppression within reasonable practical limits. This underscores the applicability of this assumption in bridging theoretical analysis and practical implementation.

Tracking Differentiator (TD):

Nonlinear:

$$\begin{cases} fv = fhan\left(v_1(k) - v, v_2(k), r_0, h\right) \\ v_1(k+1) = v_1(k) + hv_2(k) \\ v_2(k+1) = v_2(k) + hfv \end{cases}, \tag{3}$$

Linear:

$$\begin{cases} x_1(k+1) = x_1(k) + h \bullet x_2(k) \\ x_2(k+1) = x_2(k) - h \bullet \left[r^2 \bullet x_1(k) + 2r \bullet x_2(k) - r^2 v\right] \end{cases}, \tag{4}$$

where v denotes the set value, r denotes the tracking speed factor, and h denotes the filtering factor.

Extended State Observer (ESO):

$$\begin{cases} \varepsilon_1 = z_1(k) - y(k) \\ fe = fal(e, 0.5, h) \\ fe_1 = fal(e, 0.25, h) \\ z_1(k+1) = z_1(k) + hz_2(k) - \beta_{01} e \\ z_2(k+1) = z_2(k) + h\left(z_3(k) + b_0 u(k)\right) - \beta_{02} fe \\ z_3(k+1) = z_3(k) - \beta_{03} fe_1 \end{cases}, \tag{5}$$

where β_{01}, β_{02}, β_{03} is the control parameter of ESO, and its expression fal can be referred to [20,22,37] as follows:

$$fal(\varepsilon, \alpha, \delta) = \begin{cases} \dfrac{\varepsilon}{\delta^{1-\alpha}}, |\varepsilon| \le \delta \\ |\varepsilon|^{\alpha} \operatorname{sgn}(\varepsilon), |\varepsilon| > \delta \end{cases} \quad \delta > 0, \tag{6}$$

where α and δ are the parameters used in designing the controller, which need to satisfy the inequalities $0 < \alpha < 1$ and $\delta > 0$.

Control volume formation:

$$e_1 = v_1(k) - z_1(k), \tag{7}$$

$$e_2 = v_2(k) - z_2(k), \tag{8}$$

$$u(k) = u_0 - \frac{z_3(k)}{b}, \tag{9}$$

where e_1 and e_2 indicate the error between TD and ESO.

Nonlinear Feedback (NF):

Nonlinear state error feedback exists in many forms. For different control systems, the forms may be different. Two of the more common forms are listed below:

$$u_0 = \beta_1 fal(e_1, \alpha_1, \delta) + \beta_2 fal(e_2, \alpha_2, \delta), \tag{10}$$

or

$$u_0 = fhan(e_1, c \cdot e_2, r, h_1), \tag{11}$$

Figure 4 shows the structure of the PID controller, consisting of the PID controller and the controlled object. In the control system PID controller involves three independent parameters [40]—proportional value (P), integral value (I) and derivative value (D)—describing P, I and D in terms of time, i.e., P depends on the current error, I depends on the accumulation of the past error, and D is a prediction of the future error based on the current rate of change. The mathematical description of the algorithm is:

$$\begin{aligned} u(t) &= K_p\left[e(t) + \frac{1}{T_i}\int_0^t e(t)dt + T_d\frac{de(t)}{dt}\right], \\ &= K_p e(t) + K_i\int_0^t e(t)dt + K_d\frac{de(t)}{dt} \end{aligned} \tag{12}$$

where $u(t)$ is the output signal of the controller, $u(t)$ is the deviation of the input signal from the output signal, K_P is the scaling factor of the controller, T_i is the integration time of the controller, T_d is the derivation time of the controller, K_i is the integration factor of the controller, and K_d is the differentiation factor of the controller.

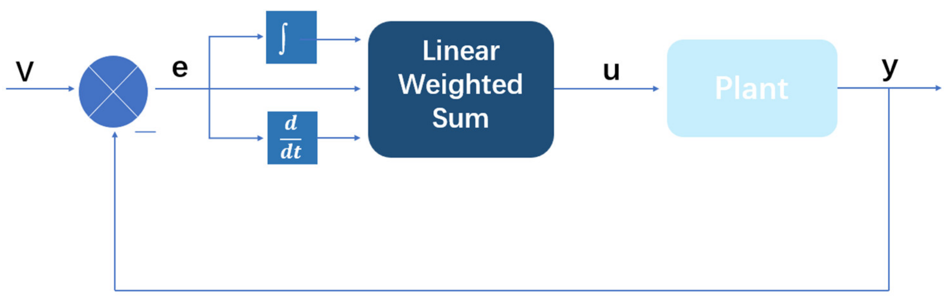


Figure 4. The structure of the PID controller.

After the Laplace transform, the transfer function can be written as:

$$G(s) = \frac{U(s)}{E(s)} = K_p\left(1 + \frac{1}{T_i s} + T_d\right), \tag{13}$$

where K_P is the proportional gain, T_i is the integration time constant, and T_d is the derivative time constant.

Unlike PID control, which needs to generate the control output by weighting the current error of the system (P), the integral of the error (I), and the differential of the error

(D), ADRC control only needs to use the inputs and outputs as the source of information without the need to build an accurate mathematical model, and generates the compensation amount of the uncertainty model to the output effect through the ESO, so that the object's uncertainty can be compensated in the feedback in order to realize the high-precision control of the system and effective suppression of disturbances [41]. Compared with PID control, ADRC focuses more on the real-time sensing and suppression of internal and external perturbations of the system, and therefore, ADRC has higher robustness and adaptivity.

2.2. Challenges and Needs in Agriculture

2.2.1. Main Challenges in the Agricultural Production Process

The unstructured working environment of agricultural production introduces significant complexity, which poses various challenging control-related issues in agricultural systems [42]. These challenges are primarily manifested in the following aspects:

- Nonlinearity of Agricultural Systems: Due to the inherent complexity of agricultural operations, agricultural systems are often nonlinear. Determining the observability and controllability of these systems is an exceedingly difficult task, requiring extensive research. The nonlinear characteristics of agricultural systems imply that their responses do not follow simple linear patterns. While linear control methods like extended Kalman filters and basic PID controllers can effectively handle basic control tasks such as autonomous navigation, automatic speed regulation, and straight-line tracking, their difficulty in parameter adjustment results in poor performance with traditional linear control methods [43].
- Time variability and Uncertainty in Agricultural Environments: Agricultural environments are often affected by seasons, weather, and other external factors, leading to time-varying or uncertain system parameters [44]. The time-varying and uncertain nature of agricultural environments make it difficult for control systems to accurately predict and adjust to these changing conditions.
- Variability of Agricultural Parameters: Agricultural systems typically involve complex interactions between multiple variables, such as soil moisture, temperature, and light intensity. This significantly increases the complexity of control systems, affecting system stability. Additionally, due to the variability of agricultural parameters and the complexity of their interactions, it is challenging to establish accurate and reasonable models [45].
- Economic Considerations in Agricultural Production: Beyond the above requirements, agricultural production must also consider energy consumption and cost-effectiveness. Therefore, control system design must involve the creation of efficient control strategies to achieve desired goals while minimizing costs.

These characteristics of agricultural production necessitate the consideration of more potential influencing factors and the development of more effective regulation methods when designing control strategies, raising the bar for research in agricultural control methodologies.

2.2.2. Limitations of Traditional Control Methods

Traditional control methods, such as PID control, Model Predictive Control (MPC), neural network control, and fuzzy control, have been continuously refined and improved through academic research. However, they still face numerous limitations when addressing the challenges posed by agricultural systems.

PID Control: This method is simple and intuitive, often used in greenhouse climate control or irrigation systems. However, PID controllers are less adaptable to nonlinear systems and are easily affected by external disturbances. In dealing with nonlinear or time-varying systems, PID controllers may underperform, as they usually require an accurate system model for parameter design, which is often difficult to obtain or accurately describe in practical applications [46]. Additionally, PID performance can be impacted by significant measurement noise or external disturbances, and it requires experienced engineers to manually tune parameters. Given the limited technical support in agricultural production, this can pose challenges in complex systems.

Model predictive control: It is widely applied in multivariable systems and control problems with constraints, thanks to its robustness and ability to handle dynamic system constraints [47]. It can be used to optimize planting cycles or irrigation strategies. However, its high computational complexity demands precise system modeling and involves solving state observation and feedback problems. In real-world applications, many systems exhibit complex nonlinearities or uncertainties, limiting MPC's effectiveness. Moreover, MPC typically requires significant computational resources for state estimation and control calculation, making it difficult to apply in resource-constrained environments or where real-time performance is critical [48].

Neural Network Control: Neural network control utilizes neural network models for system modeling and control, offering strong adaptability. However, this approach faces challenges such as high data requirements, the "black box" nature of the model, and overfitting issues. Additionally, due to differences in climate types, greenhouse structures, and crop varieties, the generalizability and adaptability of neural network models may be limited [49], making it difficult to handle the time-variability and variability inherent in agriculture.

Fuzzy Control: Fuzzy control effectively deals with complex systems that lack accurate mathematical models or exhibit significant uncertainty. Compared to traditional mathematical control methods, fuzzy control is easier to understand and tune [50,51]. However, designing and tuning fuzzy control systems is relatively complex, involving the definition of fuzzy sets, the determination of membership functions, and the formulation of rules. This complexity makes system development and optimization challenging. Additionally, the fuzzy nature of these systems may lead to decreased stability and robustness under environmental changes, noise interference, or parameter uncertainty [52]. Fuzzy control often requires substantial computational resources to perform fuzzy reasoning and rule execution, and this can lead to high computational costs when dealing with large-scale, high-dimensional problems [53].

These limitations make traditional control methods less effective in handling the complex, nonlinear, or uncertain systems typical of agricultural production.

In contrast, ADRC requires only input and output information, eliminating the need for an accurate mathematical model while still achieving high-precision control and effective disturbance rejection. Its strong robustness and adaptability give it great potential for meeting the high-precision control demands posed by unstructured agricultural working environments.

3. Application of ADRC Technology in Agriculture

3.1. Agricultural Machinery and Equipment Control

Agricultural machinery control technology is an indispensable component of modern agriculture. The application of automation and intelligent control technologies enables agricultural machinery to perform precise operations, increase production efficiency, reduce labor costs, and minimize environmental impact [54]. In the field of agricultural machinery, ADRC demonstrates significant advantages in motion control, addressing challenges posed by various unstructured environmental factors such as terrain, soil conditions, and wind direction.

Zhu et al. [55] designed an ADRC-based dual steering motion control system for a plant phenotype robot chassis to meet the agronomic needs of apple cultivation and to cope with the challenges of the complex environment in large fields on the robot's driving performance. The results of Simulink dynamics simulation experiments, steering motion simulation experiments, and field experiments show that the proposed ADRC control model's performance is significantly better than the traditional PID dual steering control model. are significantly better than the traditional PID dual steering control model. These results are highly consistent with Zhang's [56] autonomous navigation control method for agricultural vehicles based on ADRC technology, showing stronger adaptability and more stable robustness compared to her previous research [15], highlighting the superiority of ADRC.

UGVs and AGVs have numerous applications in agriculture. In addition to wheeled drives, tracked drives are also widely used in agriculture. However, due to the lack of effective slip prediction and compensation, tracked vehicles may not accurately follow the designated path in practical agricultural operations. To address this issue, Sebastian et al. [57] proposed a universal mathematical model based on the ADRC framework that can account for system state scaling and movement caused by slip by enhancing parameters. The controller designed based on this model can predict and compensate for the impact of slip on AGVs in real time. The feasibility of this approach was validated under both flat and uneven terrain conditions (including asphalt, vinyl surfaces, artificial turf, grass, and gravel), improving AGV path tracking performance and filling a gap in slip control for tracked drives in agriculture.

For tracked sprayers used in orchard pest control, the vehicle mass decreases as the spray liquid is consumed, and multi-source unknown disturbances, such as liquid sloshing in the tank, nonlinear friction, air resistance, and unmodeled system components, can affect the tracked unmanned vehicle. To address this issue, Wang et al. [58] designed a tracked orchard sprayer robot employing ADRC to enhance system noise resistance, as shown in Figure 5. This robot uses two active disturbance rejection controllers to receive the desired speed and angular velocity, outputting corresponding control signals to enhance its noise resistance. Subsequent field trials further validated the feasibility of the developed system, achieving a canopy leaf coverage rate of approximately 50% and significantly improving the robot's control accuracy.

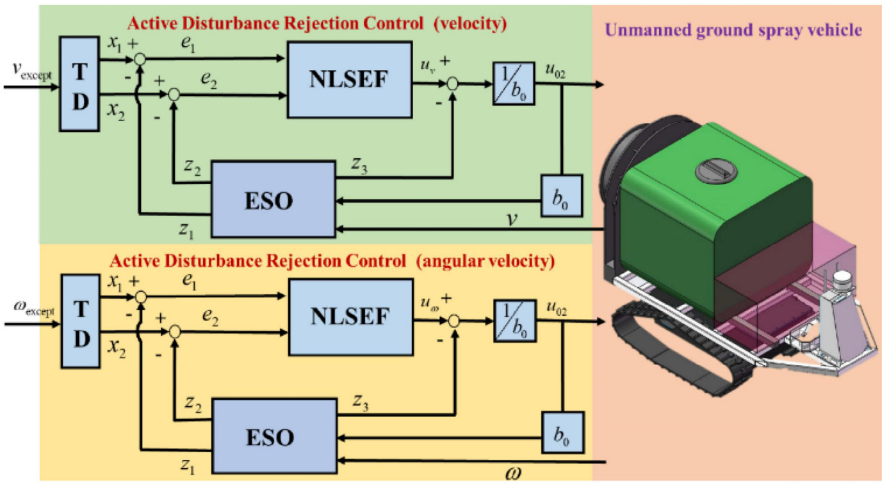


Figure 5. System control block diagram based on ADRC [58].

Similar to other equipment control research, studies on UAV control combined with ADRC often remain limited to simulations or lack practical application scenarios, with their practical utility still open to discussion. He et al. [59] proposed a parameter optimization control strategy based on ADRC to address the high requirements for attitude control in column-type plant protection UAVs, as well as various unknown disturbances and parameter uncertainties during flight. Simulation results indicated that the proposed control strategy achieved faster response and higher robustness compared to PID and Fuzzy PID controllers. However, this study lacks field trials and does not specify concrete agricultural application scenarios.

The rise and development of precision agriculture and smart agriculture impose higher requirements on the control of agricultural machinery. The control accuracy of agricultural machinery directly determines its operational quality and has a decisive impact on crop yields. Traditionally, many researchers applied classic control strategies, such as PID control, Ackermann control, and sliding mode control, to fields such as chassis motion control, heading control, and attitude control of agricultural machinery. However, with the advancement of precision and smart agriculture, agricultural machinery faces increasingly demanding performance requirements to adapt to various unstructured environmental factors such as different terrains, soil conditions, and wind directions. As a result, traditional control strategies are increasingly inadequate to meet the current needs of agricultural production.

As reviewed in Section 3.1, ADRC, with its strong robustness, high adaptability, and fast response performance, has significantly improved the control accuracy and disturbance rejection capability of agricultural machinery such as UGVs, tractors, and UAVs. Compared to traditional control strategies, ADRC is better suited for applications in complex agricultural operational environments.

3.2. Farm Navigation and Trajectory Tracking

Precise trajectory tracking control for autonomous agricultural machinery is crucial for ensuring that agricultural vehicles follow their intended paths and perform accurate agricultural tasks. Achieving rapid and precise trajectory tracking control in autonomous agricultural machinery helps reduce energy consumption, minimize crop damage, and consequently lower economic losses during agricultural production [60,61]. However, the modeling of autonomous agricultural machinery systems often involves nonlinearities and parameter uncertainties, which significantly complicate trajectory tracking control. Additionally, the complexity of field environments frequently introduces unknown external disturbances that can affect tracking accuracy.

The working environment of field wheeled follower vehicles is extremely complex and harsh, making their movement and precise positioning control technologies particularly challenging. To address this issue and improve agricultural productivity and modernization, Zhang et al. [62] designed an adaptive finite-time trajectory tracking control strategy with an adaptive extended state observer to enhance trajectory tracking accuracy and convergence speed of agricultural UGVs in complex environments. Their method, demonstrated in the MATLAB/Simulink simulation environment, outperformed traditional PID control. However, this research remains in the simulation and prototype stages, and its practical application needs further investigation.

In current rice paddy agriculture, the complexity of the operating environment leads to imprecise control issues [63], which severely limits the development of rice paddy machinery and negatively impacts the production efficiency and quality of rice and other paddy crops. Tang [64] used the Yanmar VP6E rice transplanter head as an experimental platform, automating the steering system with a parallel stepper motor and throttle control system using an electric push rod device. Based on ADRC, Tang proposed a path-tracking method with high stability and strong speed adaptability.

Autonomous orchard vehicles are becoming an essential part of modern fruit production. These robots, which must operate autonomously in complex orchard environments and perform tasks such as weeding, spraying, pruning, and harvesting, need to achieve precise trajectory tracking and adapt to uneven surfaces or harsh conditions such as wet, muddy, or snowy environments [65]. Research by Bayar et al. [66] in 2013 demonstrated the significant potential of ADRC for trajectory tracking in autonomous orchard vehicles. In subsequent research [67], they developed a slippage estimator and adapted it into a car-like robot model. Experimental results, shown in Figure 6, indicate that this method improved the accuracy and performance of orchard autonomous vehicle control systems.

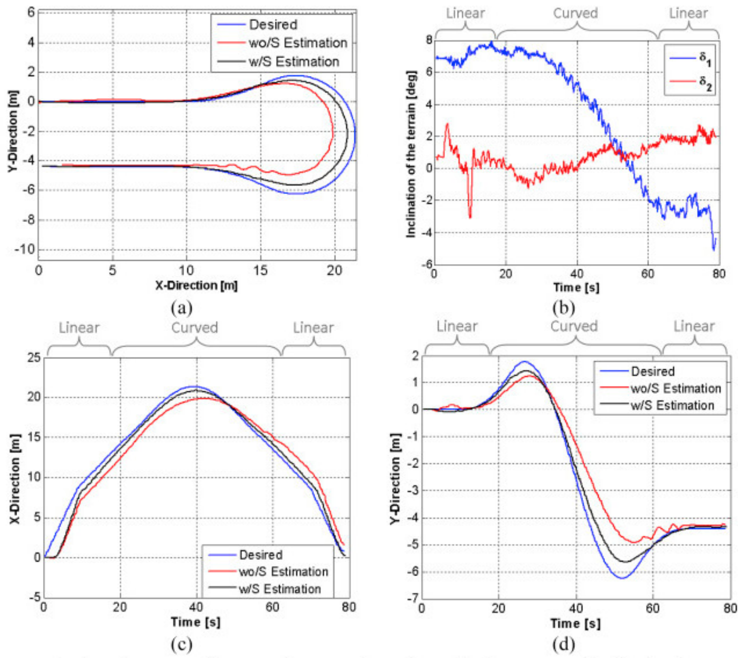


Figure 6. Trajectory tracking experiment results performed in the snowy and inclined region. (**a**) Actual trajectories, (**b**) Inclination angles of the experimental region, (**c**,**d**) Actual trajectories in longitudinal (x) and lateral (y) directions. The notations "wo/S" and "w/S" specify without and with slip estimation [68].

High-precision field navigation and path-tracking control are crucial for determining the operational quality and ecological benefits of agricultural vehicles [63]. However, conventional kinematic-based methods [69,70] often neglect vehicle dynamic parameters, such as cornering stiffness and slip angles, which can lead to reduced complexity in overall control design. While classical control strategies such as PID [71] and Pure Pursuit control [72] have demonstrated good performance in low-speed agricultural vehicle navigation and path-tracking tasks under nondisturbance conditions, they struggle with the variable road conditions and parameter uncertainties often encountered in unstructured environments of agricultural vehicles [44].

These issues make it challenging for both kinematic-based methods and classical control strategies to meet the high-precision requirements of modern precision and smart agriculture for field navigation and path tracking in agricultural vehicles. In contrast, as reviewed in Section 3.2, ADRC significantly enhances control accuracy in field navigation and path tracking due to its canonical form that transcends the boundary between linear and nonlinear systems, and its concept of extended state or total disturbance, which encompasses a broad range of uncertainties and disturbances, including model uncertainties and external unknown disturbances. This makes ADRC better suited to the development requirements and goals of precision and smart agriculture.

3.3. Agricultural Production Process Control

Process control in agricultural production is a key technology for improving production efficiency, optimizing resource utilization, and ensuring product quality in modern agriculture. The advent and development of agricultural automation have significantly reduced the time and effort required to perform repetitive tasks [73]. However, the advancement of precision agriculture has introduced new requirements for the control accuracy of various automation machinery in agricultural processes, which traditional methods like PID struggle to meet. As a result, ADRC, with its rapid response capability and strong robustness, is increasingly being applied across different agricultural processes such as sowing and weeding.

To address the complex environments of grassland and enhance the efficiency and quality of pneumatic seeders while improving their automation and precision, Chen [74] developed a kinematic model for the walking system and steering mechanism of a pneumatic seeder based on ADRC. A steering controller and path tracker were designed, and the impact of grassland terrain on seeding quality and automatic control was analyzed. The physical implementation of this research is shown in Figure 7. Field trials demonstrated that the ADRC could reduce steering adjustment time to within 2 s and achieve steering accuracy within 1°, outperforming traditional PID, and, thus, significantly improving seeding accuracy and quality.

Figure 7. Photos of steering controller performance test [74].

Most current research on weeding mechanisms focuses on horizontal rotation and swinging weeding [75]. However, during weeding operations, the actuators do not separate from the soil, which can result in the actuators failing to effectively avoid crops, thereby increasing the risk of damaging crops and their roots [76]. Researchers from South China University of Technology have integrated ADRC into both the hydraulic control system and the weeding mechanism of a weeder designed with deep learning [77]. This integration achieved minimal overshoot, with adjustment times within 1 s and steady-state error controlled to within 6 mm, effectively addressing the seedling damage caused by misalignment of the weeding components with the seedling rows.

The strong robustness and rapid response capability of ADRC have led to its successful application in crop stalk recovery, combine harvester threshing, and density-forming machines [78–80]. Lyu [78] applied ADRC to the electro–hydraulic proportional speed control system of a sweet potato vine crushing and recovery device, enhancing its disturbance resistance against variable loads during crushing and improving the stability of the vine crushing and recovery process. This application resulted in a crushing qualification rate of 89.41% and a recovery rate of 92.60%. To enhance the real-time performance, accuracy and adaptability of the threshing drum control method in sunflower combine harvesters, Zhang et al. [79] designed a control system based on ADRC and dynamic matrix models, and validated its stability in drum speed control through simulations, bench tests, and field experiments.

Harvesting robots based on mechanical arms are prone to external disturbances, such as natural conditions and collisions, which can lead to crop and branch damage as well as mechanical arm failures [81]. Therefore, developing hand–eye coordination methods for mechanical arms is crucial. Su et al. [82] proposed an advanced hand–eye coordination method based on ADRC, which exhibits strong adaptability and robustness. Given the high demands for control precision and adaptability in soft claw grasping mechanical arms for agricultural harvesting robots [83], Su et al.'s method has promising applications in this field.

In agricultural production, repetitive tasks are prevalent, making modern agriculture labor-intensive and costly. However, the quality of agricultural operations has a critical impact on yield, economic efficiency, and ecological benefits. Furthermore, precision and smart agriculture impose higher accuracy requirements on agricultural automation machinery, which traditional strategies struggle to meet. Due to its robustness, rapid response capability, ease of adjustment, and strong compatibility with other new technologies, ADRC demonstrates superior control performance in various agricultural production control tasks. The successful applications of ADRC in various agricultural production processes, as reviewed in Section 3.3, highlight its advantages over traditional control strategies and significantly enhance the effectiveness of agricultural automation machinery in complex production scenarios.

3.4. Other Agricultural Sectors

As the demand for automation and intelligent control in the agricultural sector continues to grow, ADRC, with its superior robustness and dynamic performance, has gradually been applied to a broader range of agricultural subfields. ADRC has demonstrated significant advantages in aquaculture and greenhouse management.

Aquaculture, as an integral part of agriculture, plays a crucial role in addressing global food security by enhancing the intelligence and automation of production. China, as a major aquaculture nation, accounts for more than 60% of the world's farmed aquatic products [84]. However, the development of aquaculture is still constrained by issues such as pollution caused by fish dying from natural or unnatural causes and low production efficiency. It is well known that dead fish sink to the bottom, making their removal a significant challenge for researchers. Tang et al. [85] proposed a two-degree-of-freedom underwater manipulator with an ADRC-based controller, as shown in Figure 8. This study greatly improved the system's ability to handle nonlinearities, strong coupling, and model uncertainties. Comparative experiments confirmed that the underwater manipulator employing the ADRC significantly outperformed traditional PD control and continuous sliding mode control in terms of accuracy, dynamic characteristics, and robustness. It not only enhances the intelligence and automation of aquaculture production but also improves water quality and reduces pollution caused by fish mortality, indicating the great potential of ADRC in improving water quality control.

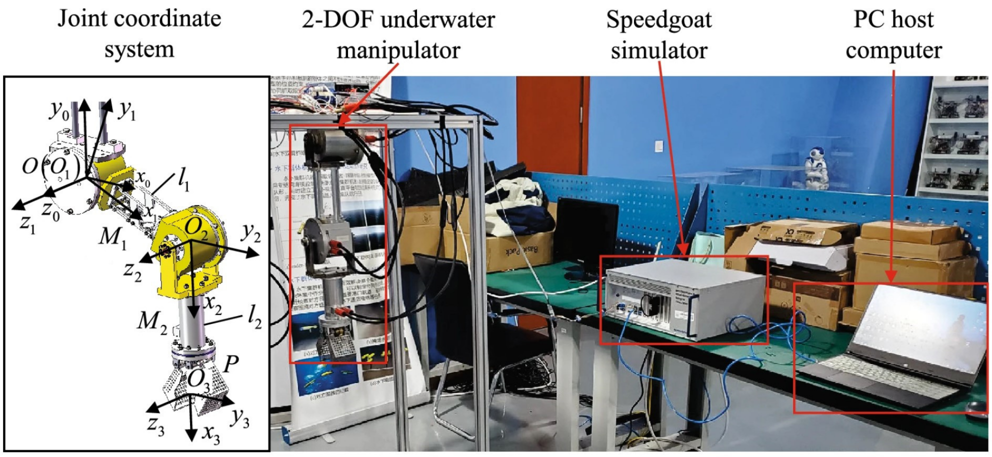


Figure 8. Underwater manipulator trajectory tracking experimental platform [85].

With the rapid advancement of science and technology, greenhouse control systems have become increasingly intelligent, evolving from simple data collection and control systems to sophisticated intelligent systems, such as expert systems [86]. In the United States, integrated greenhouse network management systems have emerged, combining climate regulation, field irrigation, and crop fertilization [87]. The introduction of such applications has undoubtedly raised new requirements for the precision, responsiveness, and robustness of intelligent greenhouse control. Meanwhile, global challenges such as energy shortages, excessive greenhouse gas emissions, and population growth have introduced additional challenges to smart greenhouse control [88,89]. Thanks to its superior characteristics, ADRC has been successfully applied in greenhouse control and is becoming a research hotspot in the field of intelligent greenhouse systems.

In response to these challenges, Xiao et al. [90] developed a greenhouse mechanism model to achieve temperature management and energy consumption reduction through intelligent control. Based on this model, they proposed two intelligent control methods: ADRC and Fuzzy ADRC. These methods regulate greenhouse temperature and energy efficiency by adjusting window openings and using heaters. Simulation results showed that the model achieved an accuracy of up to 97%. Compared to standard ADRC, the Fuzzy ADRC strategy reduced the time required to reach optimal operating conditions by 10 h during 60 h of continuous operation, decreased temperature overshoot by 60%, and saved approximately 15% in energy consumption. Although this study verified the excellent characteristics of ADRC, it lacked field experiments and did not provide comparisons with traditional control strategies like PID control, which requires further exploration.

Most of the aforementioned applications of ADRC in intelligent greenhouse control are limited to single-factor control. However, F. Garcia-Manas et al. [91] developed a two-input, two-output (TITO) model for greenhouses, utilizing a pipe heating system and a dehumidification system to regulate nighttime temperature and relative humidity. The success of this study indicates that ADRC has broader application potential in other subfields of intelligent greenhouse control, warranting further investigation.

The prospect of wide application of ADRC technology in fishery intelligence and greenhouse intelligent control tasks has been initially shown, as shown in Table 1, and its potential to address the challenges of water pollution, inefficient fishery aquaculture, global energy shortages, excessive greenhouse gas emissions, population growth, and food security has been gradually recognized. In the future, ADRC technology is expected to further promote the innovation and development of agricultural intelligence and automation.

Table 1. Comparison of ADRC and other control technologies.

Task	Models	Behavior	Result
Wheeled chassis motion control [55]	PID		ADRC significantly outperforms the PID and Ackermann models in terms of various performances such as pendulum angular velocity, turning radius and disturbance recovery time.
	Ackerman Controls		
	ADRC	√	
Agricultural vehicle heading control [15,56]	FOPID		The results of simulation experiments comparing two controllers, FOPID and ADRC, assuming constant-value perturbation and time-varying perturbation signals, show that the control performance of ADRC is more superior.
	ADRC	√	
UAV Attitude Control [59]	PID		Compared with the existing PID and Fuzzy PID methods for attitude control of plant protection drones, experimental results show that ADRC exhibits excellent adjustment capability and robustness, effectively achieving attitude control for tandem plant protection drones.
	Fuzzy PID		
	ADRC	√	

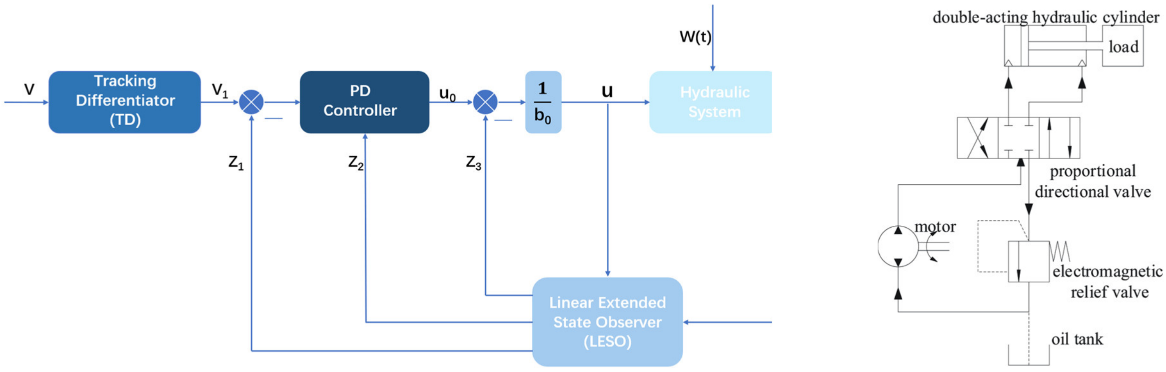
Note: Behavior column "√" indicates the better performance.

4. Application of ADRC in Combination with Other Technologies in Agriculture

4.1. Application of LADRC in Agriculture

Linear Active Disturbance Rejection Control (LADRC) is a simplified version of ADRC, in which the parameters of the controller and observer are linked to their frequency, converting the parameter tuning process into a bandwidth adjustment problem. This method was first proposed by Gao [92–94]. The advantage of LADRC lies in its independence from precise mathematical models of the system. The core idea is to use a Linear Extended State Observer (LESO) to estimate and compensate for system disturbances and uncertainties in real time, transforming the system into a cascaded integral form for control. The basic structure of LADRC is shown in Figure 9a. Compared to ADRC, LADRC introduces the concept of bandwidth, reducing the number of parameters and simplifying the tuning process, all while maintaining the performance of ADRC. This results in a much simpler structure and fewer control parameters [95,96], further enhancing the potential of ADRC across various control tasks. Owing to this advantage, LADRC has been widely applied in the agricultural sector.

In response to the rapid reaction demands of weeding operations, building on their previous research [97], Liu et al. designed a hydraulic servo system based on LADRC to reduce seedling damage rates during weeding [98]. Given that proportional directional valves often have significant input dead zones, which can greatly reduce controller performance and cause system output oscillations near the setpoint, they developed a nonlinear dead zone compensation module. Using an ESO, they proposed a residual dead zone compensation method, as illustrated in Figure 9b. Simulink simulations and experiments conducted on a platform based on the compensation method demonstrated that the system achieved a response time within 0.7 s and a steady-state error of less than 0.7 mm, significantly improving control accuracy and reducing seedling damage during weeding. However, this study remains confined to simulation and laboratory experiments, with further research needed to evaluate its effectiveness in real-world applications.



(**a**) (**b**)

Figure 9. (**a**) the basic structure diagram of LADRC; (**b**) Structure of the experimental hydraulic system [99].

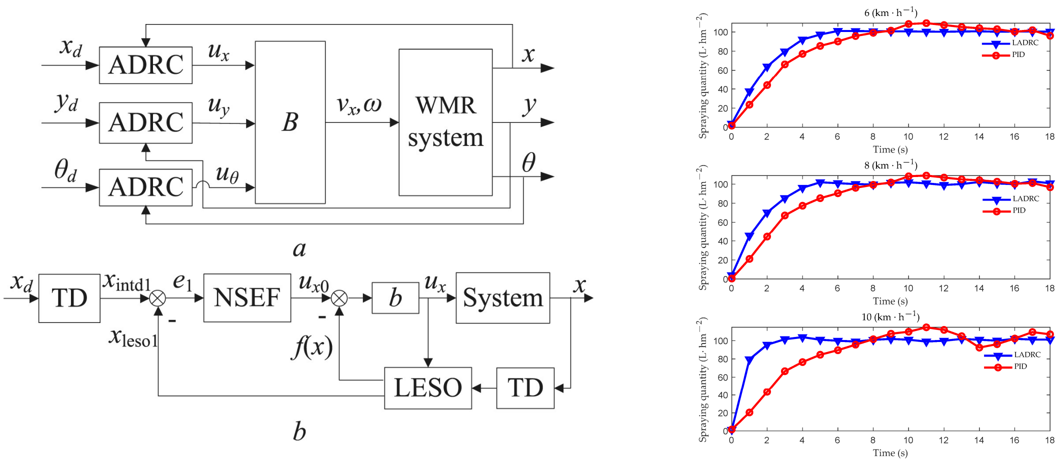
In Chen et al.'s research [99], a LADRC-based control strategy was proposed for the alignment control of a weeding mechanism. Experimental results indicated that the steady-state error was controlled within 6 mm, with almost no overshoot, and the adjustment time was kept within 1 s, filling a gap in practical field studies on LADRC's application in weeding mechanism alignment control.

In the field of motion control for agricultural machinery, LADRC has been widely applied to address the control requirements of various mobile platforms. Wang et al. [80] proposed a method to optimize LADRC parameters using the Sparrow Search Algorithm (SSA) for a mobile straw densification machine. Experimental results demonstrated that this method outperformed traditional PID control in terms of control indices like settling time and overshoot. Yu [100] designed a Decoupling Linear Active Disturbance Rejection Controller (DLADRC) for a field-following wheeled vehicle system. Based on the kinematic analysis of the relative position between the leading vehicle and the following vehicle, as well as the motion of the child vehicle and its drive motors, a mathematical model of the follower system was developed. MATLAB simulations showed that the DLADRC control strategy yielded better performance than traditional PID control in terms of overshoot, transient response time, and the average error and standard deviation of lateral and longitudinal distances between vehicles. Additionally, Xia et al. [101] developed an eight-degree-of-freedom dynamic model for a semi-tracked vehicle and proposed an LADRC controller for controlling the vehicle's vertical motion and pitch angle. Simulations of the suspension system on random road excitations indicated that LADRC provided superior control of the suspension system's acceleration and pitch angle compared to fuzzy control. Chen et al. [102] applied an improved LADRC method for path-tracking control of a six-wheeled steering vehicle on soft terrain (shown in Figure 10a), achieving excellent performance in disturbance attenuation and adjustment efficiency. This highlights LADRC's significant potential for autonomous orchard vehicles.

In UAV control, LADRC has found successful applications in attitude control, flight path planning, and load suspension systems of agricultural UAVs [102–107], improving system robustness. Mo et al. [104] applied LADRC to vertical and yaw control subsystems of UAVs with suspended loads, enhancing flight stability. Liang et al. [108] proposed two double-loop control schemes based on ADRC and LADRC to verify the anti-wind interference performance of a quadrotor UAV. Their experimental results further validated LADRC's capacity to integrate with other control methods and enhance overall performance.

Pesticide spraying is a key method for pest control in modern agriculture, and precision pesticide spraying technology can significantly improve pesticide efficiency while reducing environmental pollution, aligning with the goals of sustainable agriculture

[109,110]. However, due to complex field conditions and factors, such as acceleration and deceleration during vehicle operation, disturbances in pipeline pressure and flow can hinder accurate pesticide spraying. To address this issue, Ji et al. [111] applied LADRC to a flow control valve, using a Linear Extended State Observer (LESO) to observe total disturbances. A 12 m commercial boom sprayer was used for field testing of the proposed control strategy. The results, as shown in Figure 10b, demonstrated that the improved controller achieved a 3–5 s faster response time and a 2–9% increase in steady-state accuracy compared to PID control.



(**a**) (**b**)

Figure 10. (**a**) Block diagram of the system controller, (I) Decoupling of the system, (II) Block diagram of the improved LADRC [102]; (**b**) Field spray quantity data curve (uniform motion) [111].

In conclusion, LADRC greatly simplifies the structure and parameter tuning of ADRC with its excellent adaptability and robustness without affecting performance [95,96]. LADRC can efficiently reconstruct the system state and provide precise control, thus improving the stability and performance of the whole system, as shown in Table 2.

Table 2. Comparison of LADRC with other control technologies.

Task	Models	Behavior	Result
Straw compact mode machine water content control [80]	Smith-PID		Compared with smith-PID and smith-LADRC, SSA-Smith-LADRC has the advantages of accurate regulation, strong anti-interference ability and elimination of time lag.
	Smith-LADRC		
	SSA-Smith-LADRC	√	
Weed component to row control [99]	PID		The results show that the LADRC technique has superior anti-jamming performance in terms of row-to-row control of the weeding component, reflecting its strong robustness.
	LADRC	√	
Precision spraying of pesticides [111]	PID		Compared to traditional PID and modified PID control, LADRC controllers have greater immunity and robustness, while the difficulty of setting control parameters is greatly reduced
	Optimized PID		
	LADRC	√	

Note: Behavior column "√" indicates the better performance.

4.2. Combination of SMC and ADRC Applications in Agriculture

Sliding Mode Control (SMC) is an effective control technique for dealing with nonlinear systems. It was first proposed by Emelyanov and Filippov in the late 1950s [112], and further developed by Utkin and others [113]. Today, SMC has evolved into a well-established design method for nonlinear control systems. The basic concept involves designing a sliding surface such that once the system state reaches this surface, it remains in its vicinity [114,115]. SMC excels in responding quickly to system changes and demonstrates robustness against external disturbances and parameter uncertainties. Given the complex and dynamic nature of agriculture, along with high real-time requirements, the combined use of SMC and ADRC holds great promise in various agricultural processes.

Approximately 71% of the Earth's surface is covered by water, making water resources essential to the aquaculture industry. However, water resources are increasingly polluted [116]. In freshwater aquaculture, floating and submerged waste, such as plastic bottles and dead fish, are harmful to aquatic life. Cui et al. [117] developed a novel integral sliding mode controller (ISMC) based on a multiple-input and multiple-output extended state observer (MIMO-ESO), addressing challenges posed by unmeasured velocities, unknown disturbances, and uncertain hydrodynamics of robots. A rigorous theoretical analysis demonstrated that the proposed control method achieved asymptotic tracking performance, outperforming the traditional potential difference (PD) control method. Wang et al. [118] proposed a finite-state machine active disturbance rejection control (FSMADRC) method for controlling robotic manipulators in autonomous underwater vehicles (AUVs), achieving lower energy consumption compared to PID and fuzzy logic controllers (FLC). These studies highlight the enhanced performance of combining SMC with ADRC, particularly in aquaculture pollution mitigation.

Addressing the complexity of paddy field operations and the low level of agricultural machinery automation, Long and Li [119,120] developed a trajectory tracking and posture control model for high-clearance sprayers using sliding mode active disturbance rejection control (SADRC). They proposed a trajectory-tracking algorithm with fast response and strong anti-disturbance capabilities. Their research showed that this control strategy achieved excellent results in both simulation and real-world rice field plant protection tasks.

In addition to aquaculture, researchers have combined SMC and ADRC for agricultural tractor control. Jiang et al. [121] designed a modified sliding mode active disturbance rejection control (MSMADRC) system to address inaccuracies in the automatic mechanical transmission (AMT) shifting mechanism of small tractors. Simulation results showed that MSMADRC improved position control accuracy by 37% compared to SMC and 75% compared to ADRC, with the shortest response time of 0.7 s. Zhang et al. [122] combined nonsingular fast terminal sliding mode (NFTSM) control with a finite-time disturbance observer (FDO) to develop a control strategy for improving trajectory tracking performance in tractor straight driving and headland turning under slip conditions. This method's high precision, fast response, strong robustness, and anti-disturbance capabilities demonstrate the potential of SMC + ADRC in reducing shift times, eliminating power interruptions, and improving shift quality. However, these studies are limited to simulations and require further field testing to validate practical applicability.

In agricultural UGVs and UAV trajectory tracking, Ge et al. [123] proposed a novel adaptive sliding mode control (ASMC) method for path tracking, which enabled the lateral error of UGVs to converge to zero. The uncertainty in tire cornering stiffness was adaptively adjusted by a sliding mode observer (SMO). Both simulation and field tests indicated that ASMC provided robust performance against external disturbances, parameter uncertainties, and varying road conditions without prior road information. Zhang et al. [124] designed a sliding mode active disturbance rejection control system for a quadrotor UAV, enabling fast and accurate tracking of flight trajectories. Fu et al. [125] applied SMC + ADRC to the path tracking of USVs, proposing a TSM + ADRC control strategy and verifying its effectiveness through simulations. These studies highlight the broad application potential of SMC + ADRC in navigation and trajectory tracking for complex agricultural environments.

The combination of SMC and ADRC significantly enhances the stability and robustness of systems in complex agricultural environments, as summarized in Table 3. SMC provides strong nonlinear control capabilities, while ADRC handles system uncertainties and dynamic changes through adaptive mechanisms. This synergy not only optimizes control accuracy but also improves the system's adaptability, making it highly suitable for agricultural applications.

Table 3. Comparison of SMC + ADRC with other control technologies.

Task	Models	Behavior	Result
Underwater robot control [117]	PID		MIMO-ESO ISMC tracks the desired trajectory more accurately with less tracking bias and outperforms PD controllers in terms of peak overshoot and convergence speeds.
	MIMO-ESO ISMC	√	
Trajectory tracking for paddy sprayers [120]	PID		SADRC outperforms PD attitude control in terms of overshoot and stabilization time duration, and is able to improve sprayer trajectory tracking accuracy in complex environments
	SADRC	√	
UGV path tracing [123]	PID		The ASMC demonstrated the best tracking performance compared to the PID control and the SMC, which shows the great potential of the ADRC for UGV trajectory tracking tasks
	SMC		
	ASMC	√	

Note: Behavior column "√" indicates the better performance.

4.3. Combination of Other Technologies and ADRC Applications in Agriculture

In modern agriculture, the continuous advancement of technology and the pursuit of increased production efficiency have led to the integration of advanced control technologies into agricultural practices. ADRC, with its exceptional adaptability and robustness, is increasingly being combined with various control technologies to optimize the performance of agricultural production systems. This integration not only enhances the system's ability to adapt to environmental changes but also improves the precision of crop management, resource allocation, and production monitoring.

The world is currently facing a crisis of water scarcity, which is particularly severe in China [126]. Additionally, due to geographical and population demands, there is a shortage of agricultural irrigation water resources in China [127]. In response to the growing issue of secondary salinization in soil in some regions of China, Liu [128] applied ADRC to the flow control of water–fertilizer integrated machines and utilized the Univariate Marginal Distribution Algorithm (UMDA) to optimize the ADRC controller parameters. Simulink simulation experiments and practical tests indicated that the UMDA-ADRC control strategy outperforms traditional PID control. However, this study did not report the specific performance metrics of the optimized control, and its effectiveness requires further validation.

Wang et al. [129] addressed the high demands for attitude control during the flight of agricultural drones by proposing an Adaptive Composite Disturbance Rejection Control (ACDRC) technique. They conducted wind disturbance experiments under lateral and horizontal flows and further validated the effectiveness of their control method in vegetable and cotton fields. They also performed comparative experiments with Adaptive Disturbance Observer Control (ADOC).

Furthermore, the integration of ADRC with other techniques has seen preliminary applications in the navigation and trajectory tracking of articulated vehicles and agricultural tractors. Guevara et al. [130] designed an ADRC system with a Double-Stage Disturbance Observer (DS-DO) to improve the backward trajectory-tracking performance of Generalized N-Trailers (GNT) under nonideal conditions. The ADRC + DS-DO control method proposed was validated through simulations and field experiments. The results showed that the tracking error of ADRC + DS-DO was reduced by 57% compared to traditional ADRC, as detailed in Table 4, demonstrating its practical importance in outdoor applications and making it a potential solution for implementing automation in agricultural machinery.

Table 4. Comparison of other technologies + ADRC with traditional control technologies.

Task	Models	Behavior	Result
Fertilizer flow control [128]	PID		The superiority of the ADRC controller and the feasibility of UMDA for ADRC optimization are verified based on the actual effect of the action.
	ADRC		
	UMDA + ADRC	√	
UAV flight interference suppression [129]	ADRC		The superiority and effectiveness of the ACDRC technique in UAV anti-disturbance performance is demonstrated by indoor experiments.
	ACDRC	√	
Tractor tracking [130]	LESO		The practical importance of ADRC + DS-DO in outdoor practical applications is demonstrated, while ADRC + DS-DO provides a solution to the problem of error accumulation along the vehicle chain.
	ADRC + DS-DO	√	

Note: Behavior column "√" indicates the better performance.

In agricultural lighting systems, LED lights are commonly used in controlled agriculture to enhance crop yield. Since LED lights are DC loads while the power grid provides AC supply, a Power Factor Correction (PFC) converter is needed as an interface between the grid and LED lights. Miao et al. [131] proposed a new Boost PFC + ADRC converter control method and developed a harmonic-robust phase-locked loop scheme capable of eliminating measurement DC drift and providing harmonic robust estimation of grid voltage. Subsequently, they conducted a comprehensive simulation study varying the inclusion of a nonlinear function in the baseline PI controller. The experimental results showed that the proposed technology reduced total harmonic distortion by 42% to 65% compared to the baseline PI method, which could significantly lower the operating costs of agricultural lighting systems.

In summary, the combination of ADRC with other control technologies has demonstrated significant advantages in the agricultural field, as shown in Table 4. By integrating the adaptability and robustness of ADRC with the benefits of other control strategies, these combined technologies can significantly enhance the precision, stability, and efficiency of agricultural production systems. However, practical applications still face numerous challenges, such as system integration complexity and environmental adaptability issues. Future research should further explore the deep integration of these technologies in agricultural production to overcome existing obstacles and achieve smarter and more efficient agricultural management solutions.

5. Discussions

5.1. Advantages of ADRC Technology in Agricultural Cybernetics

The global issues of food crises, aging populations, and environmental pollution are driving countries around the world towards agricultural modernization [132–134]. Automation and intelligence in agriculture are significant markers of modern agriculture. However, traditional control methods, such as PID, model predictive control, and fuzzy control, have been difficult to adapt to the requirements of modern agricultural production operations. Since its introduction in 1999, Active Disturbance Rejection Control (ADRC) technology has achieved remarkable success across various domains, including industry, aerospace, electronics, power systems, maritime applications, healthcare, autonomous driving, and defense, demonstrating its extensive application potential. For instance, in the industrial sector, Zheng Qing et al. [135] applied ADRC to the temperature control system of an extruder in a North American factory, achieving more than a 50% reduction in energy consumption and a significant improvement in product performance. In the maritime field, Sun Xiaoming et al. [136] integrated ADRC with deep reinforcement learning to propose an enhanced method for improving ship anti-rolling performance, substantially enhancing control accuracy and response capabilities. Furthermore, Hu Xiaohao et al. [137] and Cao Guizhou et al. [23] validated the rapid response and disturbance rejection capabilities of ADRC in power systems, while Chen Gang et al. [138] utilized it in the gear-shifting control of autonomous robotic arms, significantly improving shifting accuracy. These studies underscore the exceptional advantages of ADRC in optimizing the control of complex systems [139–144], highlighting its immense potential for applications in unstructured agricultural operation scenarios.

Agriculture is the fundamental industry for producing the food necessary for human survival. It is essentially a complex system composed of multiple subsystems, including soil, water, plants, climate, and machinery. System modeling and control theory offer significant opportunities for the creation of agricultural production tools [145–148], thus promoting more manageable agricultural production. Consequently, ADRC demonstrates significant applicability in this field. This review highlights that ADRC and its improved control methods have been successfully applied across numerous agricultural areas, including agricultural equipment motion control, field navigation and trajectory tracking, agricultural production process control, aquaculture management, and smart greenhouse control. The advantages of ADRC over other control methods are summarized as follows, and the comparison results can be seen in Table 5.

Table 5. Overall comparison of ADRC with other control technologies.

Aspect	ADRC	PID	MPC	Fuzzy Control	Neural Network Control
Nonlinear Handling	★★★★★	★★	★★★★	★★★★	★★★★
Disturbance Rejection	★★★★★	★★	★★★★	★★★	★★★
Model Dependency	★★★★★	★	★★	★★★	★★★
Adaptability	★★★★★	★	★★★★	★★★	★★★★
Computational Load	★★★★	★★★★★	★★	★★★	★★
Integration Potential	★★★★★	★★	★★★★	★★★★	★★★★
Agricultural Use	★★★★★	★★	★★★★	★★★★	★★★★

Note: ★: Minimal performance or suitability; ★★★★★: Outstanding performance or suitability. ★: Represents minimal performance or suitability. ★★: Indicates limited performance or capability. ★★★: Reflects moderate effectiveness or utility. ★★★★: Denotes good performance with notable strengths. ★★★★★: Represents excellent or optimal performance, highly recommended.

- **Handling Nonlinearity of Controlled Objects:** Han's groundbreaking work on feedback system structures in 1980 [149] pointed out that, under certain conditions, dynamic systems, whether linear or nonlinear, can be transformed into a canonical form of cascade integrators through feedback. Based on this, ADRC has demonstrated its efficient control capabilities in nonlinear environments, particularly in the complex and variable field of agricultural control.
- **Handling Wide-Ranging Uncertainty and Disturbances:** Xue and Huang [150] compared ADRC with Disturbance Observer-Based Control (DOBC) and found that for systems with both model uncertainties and disturbances, ADRC and DOBC yield similar control results. However, as disturbances increase, ADRC begins to exhibit advantages by emphasizing the "total disturbance" affecting the output process rather than the disturbances entering at their original positions. This allows ADRC to

stabilize the system and shape the transient response, making it highly promising for the uncertain, disturbed, and time-variant agricultural working environments.

- **Low Dependency on Models:** One of ADRC's advantages in agriculture is low dependency on models. Agricultural environments are complex and variable, encompassing factors such as soil types, climate conditions, and crop needs. Traditional control methods often require accurate models for precise control. In contrast, ADRC estimates disturbances and uncertainties in the system in real time without relying on precise mathematical models [151]. This approach allows ADRC to remain effective even when the system model is not entirely accurate or when parameters change, enhancing the efficiency and reliability of agricultural production through its flexibility and robustness.
- **Self-Optimization and Integration with Other Control Technologies:** ADRC features superior self-optimization capabilities, enabling it to dynamically estimate external disturbances and internal states, thereby adjusting control strategies to optimize system performance. This characteristic allows it to maintain high accuracy and system stability even in uncertain environments. Additionally, ADRC's flexibility extends to its ability to effectively integrate with other control technologies. The review highlights that ADRC has been successfully combined with advanced control technologies, such as fuzzy control and neural networks, further enhancing the adaptability of control systems in uncertain and dynamic environments, and gaining widespread use in the agricultural field.

5.2. Challenges of ADRC Technology in Agricultural Cybernetics

ADRC has been widely applied in the agricultural sector and has gradually become a research focus in contemporary agricultural control theory. However, its shortcomings during practical use should not be overlooked. Based on a review of existing literature, this paper summarizes the current challenges and limitations of ADRC in agriculture as follows:

- Limited Real-World Applications: Most research on ADRC technology for agricultural machinery remains confined to simulation experiments or laboratory prototype experiments. There is a lack of field experiments in real agricultural settings, which means that some unknown factors may be overlooked in practical scenarios, leading to insufficient practical applicability of the research.
- Limited Research on UAVs: The application of ADRC in agricultural UAVs is often restricted to specific aspects of motion control. There is a lack of research on motion control performance under multi-factor disturbances. Therefore, the overall control performance of ADRC for UAVs remains to be thoroughly investigated.
- Limited Exploration in Smart Greenhouse Control: Current studies on ADRC for smart greenhouse control are mostly limited to laboratory model experiments or simulations based on software such as MATLAB and LabView. Additionally, existing research often focuses on single-factor control, such as temperature, light, or humidity. In actual greenhouse production, factors such as temperature, light, and humidity all directly affect yield and economic benefits.
- Gaps in Aquaculture Control: There remains a significant gap in the application of ADRC technology for aquaculture control.
- Focus on Navigation and Trajectory Tracking: ADRC applications in unmanned agricultural equipment are mainly focused on navigation and trajectory tracking, and not enough attention has been paid to actuator control, which needs to be further researched.

These challenges and limitations need to be thoroughly addressed in the practical application and development of ADRC to achieve optimal outcomes in the agricultural sector.

5.3. Future Directions of ADRC Technology in Agricultural Cybernetics

The application of ADRC in agriculture can be categorized into standalone applications and its integration with other technologies. This paper primarily explores ADRC in two ways: its independent application in agriculture and its combination with other control techniques. Based on the challenges identified in the agricultural application of ADRC, the following suggestions are proposed:

1. Field Applications in Agricultural Production: Building on the results from simulation and laboratory experiments, future studies should focus on conducting experiments in real-world agricultural environments such as rice paddies and cotton fields. Environmental factors like soil moisture and crop growth stages should be considered, and ADRC parameters should be optimized to adapt to these conditions. Long-term and large-scale field tests are necessary to evaluate the effectiveness of the technology, identify new challenges, and enhance its practical applicability.
2. UAV Applications: In the field of UAVs, future research should explore the simultaneous application of ADRC to UAV attitude control and payload suspension control. Improvements in control stability and precision can be achieved through algorithm enhancements, and combining ADRC with path planning and autonomous flight technologies could further extend its functionality.
3. Smart Greenhouse Control: Yield in greenhouses is directly influenced by factors such as gas concentration, lighting, and temperature. Therefore, future research should adopt ADRC strategies to simultaneously control multiple factors in smart greenhouses rather than limiting control to single variables like temperature. Integrating ADRC with sensor data and hyperspectral technology [152–154] can enable more precise control of greenhouse conditions.
4. Aquaculture Applications: ADRC has potential applications in aquaculture, including water quality control (e.g., waste removal), water environment management, and the control of feed and medication dispensing. By optimizing water quality monitoring and adjustment, and integrating with water quality sensors and automation equipment, ADRC can facilitate intelligent water quality management.
5. ADRC Optimization: Future research should explore combining ADRC techniques with intelligent algorithms and deep learning techniques. Previous research on traditional control strategies has used intelligent algorithms to optimize controller parameters [155–157]. Similarly, ADRC can benefit from combining with intelligent algorithms to improve its performance. In addition, combining ADRC with deep learning can lead to further improvements. Known for its efficiency, accuracy and robustness, deep learning has been widely used in agriculture [158–162]. By utilizing deep learning, ADRC control strategies can optimize themselves to further improve the overall performance of the ADRC system.

As ADRC becomes more widely adopted in various agricultural domains, its rapid response capabilities, strong robustness, and disturbance rejection will continue to enhance the intelligence and precision of agricultural production, ultimately increasing yields and the economic value of agriculture.

6. Conclusions

In summary, this paper provides a comprehensive review of the application of ADRC in the agricultural sector, revealing its immense potential in addressing the complex demands of modern agriculture. ADRC, with its exceptional precision, high robustness, and rapid response capabilities, has achieved significant results in various aspects such as agricultural equipment motion control, field navigation and trajectory tracking, and agricultural production process control. Researchers have also combined the advantages of ADRC with other technologies, leading to widespread applications across numerous fields.

In the domain of agricultural machinery control, ADRC has notably enhanced the control precision and disturbance rejection capability of agricultural equipment due to its outstanding robustness, significant adaptive capacity, and fast response characteristics. Compared to traditional control strategies, ADRC offers superior performance in the complex environments of agricultural operations. In field navigation and trajectory tracking, ADRC addresses external uncertainties and disturbances more efficiently through its ability to manage both linear and nonlinear systems, greatly improving the control precision of agricultural vehicles and aligning with the goals of precision and smart agriculture. In agricultural production process control, ADRC demonstrates excellent control performance owing to its robustness, quick response, convenient adjustment features, and high compatibility with emerging technologies. The successful application of ADRC in agricultural production highlights its superiority over traditional control strategies, significantly enhancing the effectiveness of automated agricultural machinery in complex production environments. Moreover, ADRC shows broad application potential in various agricultural fields, such as aquaculture and greenhouse management, and is increasingly recognized as an effective tool to address global challenges such as water quality pollution, inefficient aquaculture, global energy shortages, excessive greenhouse gas emissions, population growth, and food security.

However, current research is still primarily focused on simulation experiments and laboratory prototypes, lacking validation in large-scale and real-world application scenarios. Additionally, specific applications of ADRC in agricultural UAVs, smart greenhouse multi-factor integrated control, aquaculture, and actuator control require further investigation. To address these gaps, this paper proposes several improvement suggestions: conducting further experimental validations in actual agricultural settings, expanding research on ADRC for UAV attitude and payload control, advancing multi-factor integrated control in smart greenhouses, exploring its application in aquaculture, optimizing controller performance with intelligent algorithms, and investigating integration with deep learning technologies. These suggestions provide valuable directions for future research and emphasize the potential benefits of combining ADRC with intelligent algorithms in complex agricultural environments.

Looking ahead, with the widespread application of ADRC technology, the intelligence and precision of agricultural production will be further enhanced, leading to increased efficiency and yield in agriculture as well as significant economic and environmental benefits. Continued exploration and optimization of ADRC in agriculture will undoubtedly advance the modernization of agriculture and create a more sustainable and efficient agricultural ecosystem.

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References

1. FAO. *Food Outlook—Biannual Report on Global Food Markets*; Food Outlook: Rome, Italy, 2024.
2. Ren, H.; Wu, J.; Lin, T.; Yao, Y.; Liu, C. Research on an Intelligent Agricultural Machinery Unmanned Driving System. *Agriculture* **2023**, *13*, 1907. https://doi.org/10.3390/agriculture13101907.
3. da Silveira, F.; Lermen, F.H.; Amaral, F.G. An overview of agriculture 4.0 development: Systematic review of descriptions, technologies, barriers, advantages, and disadvantages. *Comput. Electron. Agric.* **2021**, *189*, 106405. https://doi.org/10.1016/j.compag.2021.106405.
4. Goossens, J.; Lenaerts, B.; Devos, S.; Gryllias, K.; De Ketelaere, B.; Saeys, W. Anomaly detection on the cutter bar of a combine harvester using cyclostationary analysis. *Biosyst. Eng.* **2023**, *226*, 169–181. https://doi.org/10.1016/j.biosystemseng.2023.01.013.
5. Fareh, R.; Khadraoui, S.; Abdallah, M.Y.; Baziyad, M.; Bettayeb, M. Active disturbance rejection control for robotic systems: A review. **2021**, *80*, 102671. https://doi.org/10.1016/j.mechatronics.2021.102671.
6. Chiriță, A.-P.; Pavel, C. Agricultural platform equipped with a hydrostatic transmission capable of continuously adjustable travel velocity and nonlinear disturbance compensation capabilities. *INMATEH Agric. Eng.* **2023**, *69*, 427–436. https://doi.org/10.35633/inmateh-69-40.
7. Du, Y.S.; Ma, J.; Qin, L.L.; Zhang, H.B.; Wu, G. Application of generalized predictive control algorithm for temperature control in modern greenhouse. In Proceedings of the 2016 35th Chinese Control Conference (CCC), Chengdu, China, 27–29 July 2016; pp. 4342–4347.
8. Boyu, W.; Zhenjiang, C.; Hongbo, Y.; Xuesong, S. Control Model and Experiment of Water and Fertilizer Proportion of Fertilizer Machine Based on RBF Neural Network. In Proceedings of the 2018 International Conference on Sensing, Diagnostics, Prognostics, and Control (SDPC), Xi'an, China, 15–17 August 2018; pp. 648–653.
9. Upaphai, W.; Bunyawanichakul, P.; Janthong, M. Design of Self-tuning Fuzzy PID Controllers for Position Tracking Control of Autonomous Agricultural Tractor. *Pertanika J. Sci. Technol.* **2019**, *27*, 263–280.
10. He, Z.; Gao, W.; He, X.; Wang, M.; Liu, Y.; Song, Y.; An, Z. Fuzzy intelligent control method for improving flight attitude stability of plant protection quadrotor UAV. *Int. J. Agric. Biol. Eng.* **2019**, *12*, 110–115. https://doi.org/10.25165/j.ijabe.20191206.5108.
11. Wang, Z. Greenhouse data acquisition system based on ZigBee wireless sensor network to promote the development of agricultural economy. *Environ. Technol. Innov.* **2021**, *24*, 101689. https://doi.org/10.1016/j.eti.2021.101689.
12. Li, Y.; Cao, Q.; Liu, F. Research on Fuzzy PID Control of Electronically Controlled Hydraulic Power Steering System for Unmanned Agricultural Vehicle. In Proceedings of the 2019 International Conference on High Performance Big Data and Intelligent Systems (HPBD&IS), Shenzhen, China, 9–11 May 2019; pp. 215–218.
13. Song, L.; Dong, Z.; Xiang, L.; Xing, S. Variable universe adaptive fuzzy PID control of spray flow valve. *Trans. Chin. Soc. Agric. Eng. (Trans. CSAE)* **2010**, *26*, 114–118.
14. Guo, N.; Hu, J. Variable universe adaptive fuzzy-PID control of traveling speed for rice transplanter. *Trans. Chin. Soc. Agric. Mach.* **2013**, *44*, 245–251.
15. Zhang, M.; Lin, X.; Ding, Y.; Yin, W.; Qian, Y. Design of path following controllers based on performance index for agricultural vehicle. *Trans. Chin. Soc. Agric. Eng. (Trans. CSAE)* **2012**, *28*, 40–46.
16. Yu, S.; Ma, M.; Yue, X.; Wan, H.; Wang, Y. Design and MATLAB simulation of intelligent irrigation controller based on fuzzy PID algorithm. *Water Sav. Irrig.* **2018**, *5*, 86–89.
17. Zhai, C.; Yang, S.; Wang, X.; Zhang, C.; Song, J. Status and prospect of intelligent measurement and control technology for agricultural equipment. *Trans. Chin. Soc. Agric. Mach.* **2022**, *53*, 1–20.
18. Yan, J.B.; Long, C.J.; Li, S.J. Cascade fractional order PID control of farm unmanned aerial vehicle. *J. Huazhong Agric. Univ.* **2020**, *39*, 153–158.

19. Zhang, Q. Opinion: Agricultural cybernetics, what it is, why needs it and what needs to do. *Comput. Electron. Agric.* **2024**, *217*, 108601. https://doi.org/10.1016/j.compag.2023.108601.
20. Han, J. From PID to Active Disturbance Rejection Control. *IEEE Trans. Ind. Electron.* **2009**, *56*, 900–906. https://doi.org/10.1109/tie.2008.2011621.
21. Xu, T.; Jia, L.; Wang, Z.; Song, X.; Long, T.; Wu, Z.; Duan, Z. Interval stability and ADRC of vapor cell temperature in miniaturized SERF atomic magnetometer based on light absorption. *Sens. Actuators A: Phys.* **2023**, *363*, 114753. https://doi.org/10.1016/j.sna.2023.114753.
22. Liu, L.; Liu, Y.; Zhou, L.; Wang, B.; Cheng, Z.; Fan, H. Cascade ADRC with neural network-based ESO for hypersonic vehicle. *J. Frankl. Inst.* **2022**, *360*, 9115–9138. https://doi.org/10.1016/j.jfranklin.2022.09.019.
23. Cao, G.; Zhang, X.; Li, P.; Li, F.; Liu, Y.; Wu, Z. Load frequency regulation of multi-area power systems with communication delay via cascaded improved ADRC. *Energy Rep.* **2023**, *9*, 983–991. https://doi.org/10.1016/j.egyr.2023.04.379.
24. Yuan, Z.; Wu, B.; He, J.; Fu, X.; Chen, H. Leader–follower formation source seeking control of multiple ships using sliding mode active disturbance rejection observer. *Meas. Control* **2020**, *54*, 737–747. https://doi.org/10.1177/0020294020919925.
25. Liu, H.; Xu, Z.; Qi, Z.; Li, B.; Shu, Y. Research on ADRC algorithm for longitudinal attitude of hydrofoil craft based on improved convergence law. *Ocean Eng.* **2024**, *293*, 116656. https://doi.org/10.1016/j.oceaneng.2023.116656.
26. Li, H.; He, B.; Yin, Q.; Mu, X.; Zhang, J.; Wan, J.; Wang, D.; Shen, Y. Fuzzy Optimized MFAC Based on ADRC in AUV Heading Control. *Electronics* **2019**, *8*, 608. https://doi.org/10.3390/electronics8060608.
27. Bo, Q.; Wang, P.; Chai, X.; Gong, Y.; Li, X.; Li, T.; Liu, H.; Wang, Y. Mirror milling trajectory planning for large thin-walled parts based on Fuzzy-ADRC controlled force pre-supporting. *J. Manuf. Process.* **2022**, *85*, 192–204. https://doi.org/10.1016/j.jmapro.2022.11.032.
28. Xu, Y.; Wang, X.; Liu, M.; Li, N.; Yu, T. Adaptive robust control of active magnetic bearings rigid rotor systems. *J. Power Electron.* **2023**, *23*, 1004–1015. https://doi.org/10.1007/s43236-022-00578-9.
29. Wu, X.; Jiang, D.; Yun, J.; Liu, X.; Sun, Y.; Tao, B.; Tong, X.; Xu, M.; Kong, J.; Liu, Y.; et al. Attitude Stabilization Control of Autonomous Underwater Vehicle Based on Decoupling Algorithm and PSO-ADRC. *Front. Bioeng. Biotechnol.* **2022**, *10*, 843020. https://doi.org/10.3389/fbioe.2022.843020.
30. Gheisarnejad, M.; Khooban, M.H. IoT-Based DC/DC Deep Learning Power Converter Control: Real-Time Implementation. *IEEE Trans Power Electron.* **2020**, *35*, 13621–13630.
31. Sun, R.; Mi, G. Surface temperature field of Ti-6Al and Ti-48Al alloys under continuous laser ablation. *Rare Met. Mater. Eng.* **2024**, *53*, 2405–2412.
32. Sun, R.; Mi, G.; Huang, X.; Sui, N. Molecular dynamic simulations of Ti-6Al and Fe-12Cr alloys for their heat transfer and oxygen transport behaviors. *Mod. Phys. Lett. B* **2024**, *38*, 2350263.
33. Sun, R.; Mi, G. Influence of alloying elements content on high temperature properties of Ti-V-Cr and Ti-Al-V series titanium alloys: A JMatPro program calculation study. *J. Phys.: Conf. Ser.* **2023**, *2639*, 012019.
34. Han, J.-Q. Nonlinear design methods for control systems. *IFAC Proc. Vol.* **1999**, *32*, 1531–1536. https://doi.org/10.1016/s1474-6670(17)56259-x.
35. Han, J.Q. The "extended state observer" of a class of uncertain systems. *Control Decis.* **1995**, *1*, 85–88.
36. Han, J.Q. Auto-disturbance-rejection controller and its applications. *Control Decis.* **1998**, *1*, 19–23.
37. Han, J.Q. From PID technique to active disturbance rejection control technique. *Control Eng.* **2002**, *3*, 13–18.
38. Aguilar-Ibañez, C.; Sira-Ramirez, H.; Acosta, J.Á. Stability of Active Disturbance Rejection Control for Uncertain Systems: A Lyapunov Perspective. *Int. J. Robust Nonlinear Control* **2017**, *27*, 4541–4553. https://doi.org/10.1002/rnc.3812.
39. Aguilar-Ibanez, C.; Suarez-Castanon, M.S.; Saldivar, B.; Jimenez-Lizarraga, M.A.; de Jesus Rubio, J.; Mendoza-Mendoza, J. Algebraic Active Disturbance Rejection to Control a Generalized Uncertain Second-Order Flat System. *Int. J. Appl. Math. Comput. Sci.* **2024**, *34*, 185–198. https://doi.org/10.61822/amcs-2024-0013.
40. Guo, Q.; Jiang, D. Moving Process PID Control in Robots' Field. In Proceedings of the 2012 International Conference on Control Engineering and Communication Technology (ICCECT), Shenyang, China, 7–9 December 2012; pp. 386–389.
41. Li, K.; Wang, Y.; Zhou, X.; Ma, Y. Application of Active Disturbance Rejection Technology in Boost Converter. In Proceedings of the 2019 IEEE International Conference on Mechatronics and Automation (ICMA), Tianjin, China, 4–7 August 2019; pp. 1178–1183.
42. Huang, Y.; Xue, W. Active disturbance rejection control: Methodology and theoretical analysis. *ISA Trans.* **2014**, *53*, 963–976. https://doi.org/10.1016/j.isatra.2014.03.003.

43. Liu, Y.; Wang, J.; Shi, Y.; He, Z.; Liu, F.; Kong, W.; He, Y. Unmanned airboat technology and applications in environment and agriculture. *Comput. Electron. Agric.* **2022**, *197*, 106920. https://doi.org/10.1016/j.compag.2022.106920.
44. Jin, X.; Zhao, Y.; Wang, H.; Zhao, Z.; Dong, X. Adaptive fault-tolerant control of mobile robots with actuator faults and unknown parameters. *IET Control Theory Appl.* **2019**, *13*, 1665–1672. https://doi.org/10.1049/iet-cta.2018.5492.
45. Wang, H.; Noguchi, N. Adaptive turning control for an agricultural robot tractor. *Int. J. Agric. Biol. Eng.* **2018**, *11*, 113–119. https://doi.org/10.25165/j.ijabe.20181106.3605.
46. Sun, B. An Algorithm Research of an Adaptive PID Control. Ph.D. Dissertation, Changchun University of Technology, Changchun, China, 2014.
47. Zhang, T.; Li, M.; Li, D.; Zhang, Y.; Yan, K. The research of MPC in secondary cooling system of battery. *J. Eng. Thermophys.* **2024**, *45*, 13–19.
48. Zhang, P.J.; Wu, J.G. Simulation Study of Predictive Functional Control Based on Characteristic Model. *J. Syst. Simul.* **2008**, *1*, 2–9.
49. Hu, J.; Yang, Y.; Li, Y.; Hou, J.; Sun, Z.; Wang, H.; He, D. Analysis and prospect of the environmental control systems for greenhouse. *Trans. Chin. Soc. Agric. Eng. (Trans. CSAE)* **2024**, *40*, 112–128.
50. Mamdani, E.H.; Assilian, S. An experiment in linguistic synthesis with a fuzzy logic controller. *Int. J. Man-Mach. Stud.* **1975**, *7*, 1–13. https://doi.org/10.1016/S0020-7373(75)80002-2.
51. Lee, C.C. Fuzzy Logic in Control Systems: Fuzzy Logic Controller-Part I. *IEEE Trans. Syst. Man Cybern.* **1990**, *20*, 404–418.
52. Tahani, V.; Sheikholeslam, F. Stability Analysis and Design of Fuzzy Control Systems. In Proceedings of the 1998 IEEE International Conference on Fuzzy Systems Proceedings. IEEE World Congress on Computational Intelligence, Anchorage, AK, USA, 4–9 May 1998; pp. 456–461.
53. Wang, L.-X.; Mendel, J. Generating Fuzzy Rules by Learning from examples. *IEEE Trans. Syst. Man Cybern.* **1992**, *22*, 1414–1427. https://doi.org/10.1109/21.199466.
54. Liu, C.; Lin, H.; Li, Y.; Gong, L.; Miao, Z. Analysis on Status and Development Trend of Intelligent Control Technology for Agricultural Equipment. *Trans. Chin. Soc. Agric. Mach.* **2020**, *51*, 1–18.
55. Zhu, L.; Zhao, Z.; Han, Z.; Wang, R.; Zhou, L.; Zhao, B. Design and experiment of dual-steering control system based on active disturbance rejection control. *Trans. Chin. Soc. Agric. Mach.* **2023**, *54*, 391–401.
56. Zhang, M.N. Research on Autonomous Guidance Control Algorithms for Agricultural Vehicles. Ph.D. Dissertation, Nanjing Agricultural University, Nanjing, China, 2013.
57. Sebastian, B.; Ben-Tzvi, P. Active Disturbance Rejection Control for Handling Slip in Tracked Vehicle Locomotion. *J. Mech. Robot.* **2019**, *11*, 021003. https://doi.org/10.1115/1.4042347.
58. Wang, S.; Song, J.; Qi, P.; Yuan, C.; Wu, H.; Zhang, L.; Liu, W.; Liu, Y.; He, X. Design and development of orchard autonomous navigation spray system. *Front. Plant Sci.* **2022**, *13*, 960686. https://doi.org/10.3389/fpls.2022.960686.
59. He, Z.H.; Gao, W.L.; He, X.K.; Wang, M.J.; Song, Y. Attitude control for tandem plant protection UAV based on fuzzy parameter optimization of active disturbance rejection control. *J. Jiangsu Univ. (Nat. Sci. Ed.)* **2021**, *42*, 198–206.
60. de Bruin, S.; Lerink, P.; La Riviere, I.J.; Vanmeulebrouk, B. Systematic planning and cultivation of agricultural fields using a geo-spatial arable field optimization service: Opportunities and obstacles. *Biosyst. Eng.* **2014**, *120*, 15–24.
61. Bacco, M.; Barsocchi, P.; Ferro, E.; Gotta, A.; Ruggeri, M. The Digitisation of Agriculture: A Survey of Research Activities on Smart Farming. *Array* **2019**, *3–4*, 100009. https://doi.org/10.1016/j.array.2019.100009.
62. Zhang, T.; Jiao, X.; Wang, Z.; Lin, Z. Improving trajectory tracking performance of autonomous farming vehicles using adaptive extended state observer and finite-time technique. *Trans. Inst. Meas. Control* **2022**, *45*, 146–156. https://doi.org/10.1177/01423312221111614.
63. Tian, L.; Cao, C.; Qin, K.; Fang, L.; Ge, J. Design and test of post-seat weeding machine for paddy. *Int. J. Agric. Biol. Eng.* **2021**, *14*, 97–105. https://doi.org/10.25165/j.ijabe.20211403.5936.
64. Tang, X.T. Research on Navigation Control System of Rice Planter. Ph.D. Dissertation, Shanghai Jiao Tong University, Shanghai, China, 2018.
65. Bayar, G.; Bergerman, M.; Koku, A.B.; Konukseven, E.I. Localization and control of an autonomous orchard vehicle. *Comput. Electron. Agric.* **2015**, *115*, 118–128. https://doi.org/10.1016/j.compag.2015.05.015.
66. Bayar, G. Long distance autonomous trajectory tracking for an orchard vehicle. *Ind. Robot Int. J. Robot. Res. Appl.* **2013**, *40*, 27–40. https://doi.org/10.1108/01439911311294237.
67. Bayar, G.; Bergerman, M.; Konukseven, E.I.; Koku, A.B. Improving the trajectory tracking performance of autonomous orchard vehicles using wheel slip compensation. *Biosyst. Eng.* **2016**, *146*, 149–164. https://doi.org/10.1016/j.biosystemseng.2015.12.019.

68. Xie, D.; Chen, L.; Liu, L.; Chen, L.; Wang, H. Actuators and Sensors for Application in Agricultural Robots: A Review. *Machines* **2022**, *10*, 913. https://doi.org/10.3390/machines10100913.
69. Hu, J.; Zhang, Y.; Rakheja, S. Adaptive Trajectory Tracking for Car-Like Vehicles with Input Constraints. *IEEE Trans. Ind. Electron.* **2021**, *69*, 2801–2810. https://doi.org/10.1109/tie.2021.3068672.
70. Jing, Y.; Liu, G.; Luo, C. Path tracking control with slip compensation of a global navigation satellite system based trac-tor-scraper land levelling system. *Biosyst. Eng.* **2021**, *212*, 360–377.
71. Khalaji, A.K. PID-based target tracking control of a tractor-trailer mobile robot. *Proc. Inst. Mech. Eng. Part C: J. Mech. Eng. Sci.* **2019**, *233*, 4776–4787. https://doi.org/10.1177/0954406219830438.
72. Yang, Y.; Li, Y.; Wen, X.; Zhang, G.; Ma, Q.; Cheng, S.; Qi, J.; Xu, L.; Chen, L. An optimal goal point determination algorithm for automatic navigation of agricultural machinery: Improving the tracking accuracy of the Pure Pursuit algorithm. *Comput. Electron. Agric.* **2022**, *194*, 106760. https://doi.org/10.1016/j.compag.2022.106760.
73. Naik, N.S.; Shete, V.V.; Danve, S.R. Precision agriculture robot for seeding function. In Proceedings of the 2016 International Conference on Inventive Computation Technologies (ICICT), Coimbatore, India, 26–27 August 2016; pp. 1–3.
74. Chen, Y. Study on Variable Spraying Technology and Relative Parameters Optimization of Spray Seeding Machine Based on Multi-Source Information. Ph.D. Dissertation, Inner Mongolia Agricultural University, Hohhot, China, 2018.
75. Quan, L.; Jiang, W.; Li, H.; Li, H.; Wang, Q.; Chen, L. Intelligent intra-row robotic weeding system combining deep learning technology with a targeted weeding mode. *Biosyst. Eng.* **2022**, *216*, 13–31. https://doi.org/10.1016/j.biosystemseng.2022.01.019.
76. Heisel, T.; Andreasen, C.; Christensen, S. Sugarbeet yield response to competition from *Sinapis arvensis* or *Lolium perenne* growing at three different distances from the beet and removed at various times during early growth. *Weed Res.* **2002**, *42*, 406–413. https://doi.org/10.1046/j.1365-3180.2002.00301.x.
77. Yang, Y. Deep-Learning-Based Intelligent Navigation and Active Disturbance Rejection Control of Weeders. Ph.D. Dissertation, South China University of Technology, Guangzhou, China, 2021.
78. Lv, H.Y. Design and Test of Sweet Potato Vine Recovery and Crushing Device and Control System. Ph.D. Dissertation, Shandong Agricultural University, Tai'an, China, 2021.
79. Zhang, X.; Li, X.; Zhu, X.; Ma, S. Rotational speed control of threshing cylinder of oil sunflower combine harvester based on active disturbance rejection controller-dynamic matrix predictive. *Trans. Chin. Soc. Agric. Eng. (Trans. CSAE)* **2019**, *35*, 9–16.
80. Wang, W.; Gong, Y.; Bai, X.; Tan, R.; Li, N.; Li, H. Straw moisture content control system of mobile straw compactor. *Trans. Chin. Soc. Agric. Mach.* **2023**, *54*, 386–393.
81. Liu, J.; Liang, J.; Zhao, S.; Jiang, Y.; Wang, J.; Jin, Y. Design of a Virtual Multi-Interaction Operation System for Hand–Eye Coordination of Grape Harvesting Robots. *Agronomy* **2023**, *13*, 829.
82. Su, J.; Qiu, W.; Ma, H.; Woo, P.-Y. Calibration-free robotic eye-hand coordination based on an auto disturbance-rejection controller. *IEEE Trans. Robot.* **2004**, *20*, 899–907. https://doi.org/10.1109/tro.2004.829458.
83. Liu, Y.; Hou, J.; Li, C.; Wang, X. Intelligent Soft Robotic Grippers for Agricultural and Food Product Handling: A Brief Review with a Focus on Design and Control. *Adv. Intell. Syst.* **2023**, *5*. https://doi.org/10.1002/aisy.202300233.
84. Liu, S.J.; Li, G.D.; Liu, H.; Zheng, H.; Chen, J. Current development status of aquaculture equipment in China. *J. Fish.* **2023**, *47*, 188–201.
85. Tang, Q.; Jin, D.; Luo, R.; Tao, R.; Li, C.; Li, J.; Liu, M.; Wang, C. Tracking control of an underwater manipulator using active disturbance rejection. *J. Mar. Sci. Technol.* **2023**, *28*, 770–783. https://doi.org/10.1007/s00773-023-00956-3.
86. Yang, S.; Wang, J.; Li, M.; Yue, H. Research on Intellectualized Location of Coal Gangue Logistics Nodes Based on Particle Swarm Optimization and Quasi-Newton Algorithm. *Mathematics* **2022**, *10*, 162. https://doi.org/10.3390/math10010162.
87. Tian, Y. Adaptive control and supply chain management of intelligent agricultural greenhouse by intelligent fuzzy auxiliary cognitive system. *Expert Syst.* **2022**, *41*, e13117. https://doi.org/10.1111/exsy.13117.
88. Pay, M.L.; Kim, D.W.; E Somers, D.; Kim, J.K.; Foo, M. Modelling of plant circadian clock for characterizing hypocotyl growth under different light quality conditions. *In Silico Plants* **2022**, *4*, diac001. https://doi.org/10.1093/insilicoplants/diac001.
89. Poore, J.; Nemecek, T. Reducing food's environmental impacts through producers and consumers. *Science* **2018**, *360*, 987–992. https://doi.org/10.1126/science.aaq0216.
90. Fei, X.; Xiao-Long, W.; Yong, X. Development of Energy Saving and Rapid Temperature Control Technology for Intelligent Greenhouses. *IEEE Access* **2021**, *9*, 29677–29685. https://doi.org/10.1109/access.2021.3059199.
91. García-Mañas, F.; Hägglund, T.; Guzmán, J.; Rodríguez, F.; Berenguel, M. Multivariable control of nighttime temperature and humidity in greenhouses combining heating and dehumidification. *IFAC-PapersOnLine* **2023**, *56*, 9900–9905. https://doi.org/10.1016/j.ifacol.2023.10.668.

92. Gao, Z. Scaling and bandwidth-parameterization based controller tuning. In Proceedings of the 2003 American Control Conference, Denver, CO, USA, 4–6 June 2003; pp. 4989–4996. https://doi.org/10.1109/acc.2003.1242516.
93. Gao, Z. On the problem of information in engineering cybernetics. *J. Syst. Sci. Math. Sci. Chin. Ser.* **2016**, *36*, 908.
94. Gao, Z. On the foundation of active disturbance rejection control. *Control Theory Technol.* **2013**, *30*, 1498–1510.
95. Ai, S.; Song, J.; Cai, G. A real-time fault diagnosis method for hypersonic air vehicle with sensor fault based on the auto temporal convolutional network. *Aerosp. Sci. Technol.* **2021**, *119*, 107220. https://doi.org/10.1016/j.ast.2021.107220.
96. Gao, K.; Song, J.; Wang, X.; Li, H. Fractional-order proportional-integral-derivative linear active disturbance rejection control design and parameter optimization for hypersonic vehicles with actuator faults. *Tsinghua Sci. Technol.* **2021**, *26*, 9–23. https://doi.org/10.26599/tst.2019.9010041.
97. Liu, F.; Yang, Y.; Zeng, Y.; Liu, Z. Bending diagnosis of rice seedling lines and guidance line extraction of automatic weeding equipment in paddy field. *Mech. Syst. Signal Process.* **2020**, *142*, 106791. https://doi.org/10.1016/j.ymssp.2020.106791.
98. Liu, F.; Yang, Y.; Wang, L. Active Disturbance Rejection Control Design for the Hydraulic Actuator on Weeding Machine. In Proceedings of the 2021 40th Chinese Control Conference (CCC), Shanghai, China, 26–28 July 2021; pp. 3822–3827.
99. Chen, X.; Fang, G.; Ma, X.; Jiang, Y.; Qi, L.; Huang, Z. Design and experiment of control system for weeding alignment in rice field based on linear active disturbance rejection control. *Trans. Chin. Soc. Agric. Eng. (Trans. CSAE)* **2020**, *36*, 19–27.
100. Yu, J.M. The Development of Field-Wheeled Following Vehicle Control System in View of Decoupling Linear Active Disturbance Rejection Control Technology. Ph.D. Dissertation, Fujian Agriculture and Forestry University, Fuzhou, China, 2013.
101. Xia, Y.; Xu, Y.; Pu, F.; Fu, M. Active disturbance rejection control for active suspension system of tracked vehicles. In Proceedings of the 2016 IEEE International Conference on Industrial Technology (ICIT), Taipei, Taiwan, 14–17 March 2016; pp. 1760–1764.
102. Chen, C.; Gao, H.; Ding, L.; Li, W.; Yu, H.; Deng, Z. Trajectory tracking control of WMRs with lateral and longitudinal slippage based on active disturbance rejection control. *Robot. Auton. Syst.* **2018**, *107*, 236–245. https://doi.org/10.1016/j.robot.2018.06.011.
103. Zhang, S.; Xue, X.; Chen, C.; Sun, Z.; Sun, T. Development of a low-cost quadrotor UAV based on ADRC for agricultural remote sensing. *Int. J. Agric. Biol. Eng.* **2019**, *12*, 82–87. https://doi.org/10.25165/j.ijabe.20191204.4641.
104. Mo, R.; Geng, Q.; Lu, X. Study on control method of a rotor UAV transportation with slung-load. In Proceedings of the 2016 35th Chinese Control Conference (CCC), Chengdu, China, 27–29 July 2016; pp. 3274–3279.
105. Pei, X.; Wu, H.; Ma, P.; Yan, Y.; Hao, P.; Bai, Y. Design and experiment of multi-rotor UAV control system with spectral remote sensing load. *Infrared Laser Eng.* **2019**, *48*, 118003.
106. Wang, S.; Han, Y.; Chen, J.; Zhang, Z.; Liu, X. Active disturbance rejection control of UAV attitude based on iterative learning control. *Acta Aeronaut. Astronaut. Sin.* **2020**, *41*, 324112.
107. Jiang, X. Research on Robustness of Autonomous Flight Control of Rotor Type Plant Protection UAV. Ph.D. Dissertation, Xi'an University of Architecture and Technology, Xi'an, China, 2019.
108. Liang, H.; Xu, Y.; Yu, X. ADRC vs. LADRC for quadrotor UAV with wind disturbances. In Proceedings of the 2019 Chinese Control Conference (CCC), Guangzhou, China, 27–30 July 2019; pp. 8037–8043.
109. He, X.; Bonds, J.; Herbst, A.; Langenakens, J. Recent development of unmanned aerial vehicle for plant protection in East Asia. *Int. J. Agric. Biol. Eng.* **2017**, *10*, 18–30.
110. Zhang, Q.; Wang, W.; Liao, J. Design and Finite Element Analysis of a Fertilizing Machine's Furrow Opener in Jujube Orchard. *J. Agric. Mech. Res.* 2016, *38*, 23–28.DOI:10.13427/j.cnki.njyi.2016.04.005
111. Ji, X.; Wang, A.; Wei, X. Precision Control of Spraying Quantity Based on Linear Active Disturbance Rejection Control Method. *Agriculture* **2021**, *11*, 761. https://doi.org/10.3390/agriculture11080761.
112. Filippov, A.F. Differential Equations with Discontinuous Righthand Sides. *Math. Its Appl.* **1960**, *99*, 99–128.
113. Utkin, V. Variable structure systems with sliding modes. *IEEE Trans. Autom. Control* **1977**, *22*, 212–222.
114. Jin-Kun, L.; Fu-Chun, S. Research and development on theory and algorithms of sliding mode control. *Control Theory Appl.* **2007**, *24*, 407–418.
115. Edwards, C.; Spurgeon, S.K. *Sliding Mode Control: Theory and Applications*; CRC Press: London, UK, 1998.
116. Bhuvanesh, N.; Kumaresan, G.; Renuka, K.; Mukeshu, R.; Hakeem, M.; Harish, V.N.N. Investigation on development and performance analysis of water trash collector. *Mater. Today Proc.* **2022**, *66*, 1216–1220.
117. Cui, R.; Chen, L.; Yang, C.; Chen, M. Extended State Observer-Based Integral Sliding Mode Control for an Underwater Robot with Unknown Disturbances and Uncertain Nonlinearities. *IEEE Trans. Ind. Electron.* **2017**, *64*, 6785–6795. https://doi.org/10.1109/tie.2017.2694410.
118. Wang, H.D.; Li, X.G.; Liu, X.; Karkoub, M.; Zhou, L.Q. Fuzzy Sliding Mode Active Disturbance Rejection Control of an Autonomous Underwater Vehicle-Manipulator System. *J. Ocean Univ. China* **2020**, *19*, 1081–1093.

119. Long, Y.N. Design and Control of the Steering System for High-Cleared Unmanned Sprayers. Ph.D. Dissertation, Jiangsu University: Zhenjiang, China, 2021.
120. Li, C.H. Trajectory Tracking and Attitude Control of the Synchronously Steering High Clearance Sprayer. Ph.D. Dissertation, Jiangsu University, Zhenjiang, China, 2022.
121. Jiang, C.; Yin, C.; Gao, J.; Yuan, G. Position Control of Gear Shift based on Sliding Mode Active Disturbance Rejection Control for Small-Sized Tractors. *Sci. Prog.* **2022**, *105*. doi:10.1177/00368504221081966 .
122. Zhang, T.; Jiao, X.; Lin, Z. Finite time trajectory tracking control of autonomous agricultural tractor integrated nonsingular fast terminal sliding mode and disturbance observer. *Biosyst. Eng.* **2022**, *219*, 153–164. https://doi.org/10.1016/j.biosystemseng.2022.04.020.
123. Ge, Z.; Man, Z.; Wang, Z.; Bai, X.; Wang, X.; Xiong, F.; Li, D. Robust adaptive sliding mode control for path tracking of unmanned agricultural vehicles. *Comput. Electr. Eng.* **2023**, *108*, 108693. https://doi.org/10.1016/j.compeleceng.2023.108693.
124. Zhang, Y.; Chen, Z.; Sun, M.; Zhang, X. Trajectory tracking control of a quadrotor UAV based on sliding mode active disturbance rejection control. *Nonlinear Anal. Model. Control* **2019**, *24*, 545–560. https://doi.org/10.15388/na.2019.4.4.
125. Fu, M.; Wu, S.; Xu, Y. Active Disturbance Rejection Sliding Mode Control for USV Path Tracking. In Proceedings of the 2020 39th Chinese Control Conference (CCC), Shenyang, China, 27–29 July 2020; pp. 2590–2596.
126. Zhang, T. China to implement the strictest water conservation measures. *Ecol. Econ.* **2023**, *39*, 9–12.
127. Qian, Y.; Dong, H.; Tian, X.; Yu, Y.; Chen, Y.; Geng, Y.; Zhong, S.A. A review of the research on China's water footprint responding to water crisis. *Ecol. Econ.* **2018**, *34*, 162–166.
128. Liu, Q.F. Research and Application of Advanced Control Technologies for Water and Fertilizer Integrated Machine. Ph.D. Dissertation, Northeastern University, Shenyang, China, 2018.
129. Wang, S.; Chen, J.; He, X. An adaptive composite disturbance rejection for attitude control of the agricultural quadrotor UAV. *ISA Trans.* **2022**, *129*, 564–579. https://doi.org/10.1016/j.isatra.2022.01.012.
130. Guevara, L.; Jorquera, F.; Walas, K.; Auat-Cheein, F. Robust control strategy for generalized N-trailer vehicles based on a dual-stage disturbance observer. *Control Eng. Pract.* **2022**, *131*, 105382. https://doi.org/10.1016/j.conengprac.2022.105382.
131. Pay, M.L.; Christensen, J.; He, F.; Roden, L.; Ahmed, H.; Foo, M. PLL-based Enhanced Control of Boost PFC Converter for Smart Farming Lighting Application. *Renew. Energy Focus* **2023**, *47*, 100502. https://doi.org/10.1016/j.ref.2023.100502.
132. Zhao, M.J.; Zhou, C.H. High-quality promotion of green agricultural development: Multi-objective synergy and multi-centered governance. *J. China Agric. Univ. (Soc. Sci. Ed.)* **2024**, 1–16, DOI:10.13240/j.cnki.caujsse.20240802.002.
133. Li, N.; Li, Y.L. Digitally empowered agricultural modernization: Intrinsic mechanism, effectiveness review, and practical direction. *J. Huazhong Agric. Univ. (Soc. Sci. Ed.)* **2024**, 1–12,DOI:10.13300/j.cnki.hnwkxb.2024.05.004.
134. Wang, Y. Impact of digital new quality productivity on agricultural and rural modernization: Index system con-struction and effect test. *Stat. Decis.* **2024**, *40*, 23–28.
135. Zheng, Q.; Gao, Z. An energy saving, factory-validated disturbance decoupling control design for extrusion processes. In Proceedings of the 2012 10th World Congress on Intelligent Control and Automation (WCICA 2012), Beijing, China, 6–8 July 2012; pp. 2891–2896.
136. Sun, M.; Zhang, W.; Zhang, Y.; Luan, T.; Yuan, X.; Li, X. An anti-rolling control method of rudder fin system based on ADRC decoupling and DDPG parameter adjustment. *Ocean Eng.* **2023**, *278*, 114306. https://doi.org/10.1016/j.oceaneng.2023.114306.
137. Hu, X.; Shao, W.; Cheng, Y.; Zhang, C.; Han, Y. Research on ADRC controller of bidirectional DC–DC converter for MMC-BESS. *Energy Rep.* **2023**, *9*, 1627–1636.
138. Chen, G.; Chen, Z.; Wang, L.; Zhang, W. Deep Deterministic Policy Gradient and Active Disturbance Rejection Controller based coordinated control for gearshift manipulator of driving robot. *Eng. Appl. Artif. Intell.* **2022**, *117*, 105586. https://doi.org/10.1016/j.engappai.2022.105586.
139. Wu, Y.; Zheng, Q. ADRC or adaptive controller—A simulation study on artificial blood pump. *Comput. Biol. Med.* **2015**, *66*, 135–143. https://doi.org/10.1016/j.compbiomed.2015.09.006.
140. Hu, Y.; Wu, M.; Zhao, K.; Song, J.; He, B. ADRC-based compound control strategy for spacecraft multi-body separation. *Aerosp. Sci. Technol.* **2023**, *143*, 108686. https://doi.org/10.1016/j.ast.2023.108686.
141. Xia, Y.; Dai, L.; Fu, M.; Li, C.; Wang, C. Application of active disturbance rejection control in tank gun control system. *J. Frankl. Inst.* **2014**, *351*, 2299–2314. https://doi.org/10.1016/j.jfranklin.2013.02.003.
142. Shen, Z. Design and Simulation of Naval Gun Servo Controller Based on ADRC. In Proceedings of the 2019 11th International Conference on Measuring Technology and Mechatronics Automation (ICMTMA), Qiqihar, China, 28–29 April 2019; pp. 345–349.

143. Wu, D.; Yuan, K.; Huang, Y.; Yuan, Z.-M.; Hua, L. Design and test of an improved active disturbance rejection control system for water sampling unmanned surface vehicle. *Ocean Eng.* **2022**, *245*, 110367. https://doi.org/10.1016/j.oceaneng.2021.110367.
144. Zhou, X.; Cui, H.; Ma, Y.; Gao, Z. The research on energy conservation controller for asynchronous motor based on ADRC. In Proceedings of the 2017 29th Chinese Control and Decision Conference (CCDC), Chongqing, China, 28–30 May 2017; pp. 4010–4014.
145. Shen, Y.; Zhang, Y.; Liu, H.; He, S.; Feng, R.; Wan, Y. Research review of agricultural equipment automatic control technology. *Trans. Chin. Soc. Agric. Mach.* **2023**, *54*, 1–18.
146. Zhang, X.N. Application of intelligent control engineering in agricultural technology—Review of "Research on the development dynamics of intelligent control systems for agricultural equipment". *Chin. Agric. Meteorol.* **2021**, *42*, 166.
147. Wang, Z.; Wang, R.-F.; Wang, M.; Lai, T.; Zhang, M. Self-supervised transformer-based pre-training method with General Plant Infection dataset. In *Pattern Recognition and Computer Vision. PRCV 2024*; Springer: Singapore, 2024.
148. Yao, M.; Huo, Y.; Ran, Y.; Tian, Q.; Wang, R.-F.; Wang, H. Neural Radiance Field-based Visual Rendering: A Comprehensive Review. *arXiv* **2024**, arXiv:2404.00714.
149. Han, J.Q. Duality in linear control systems. *Math. Ann. A (Chin. Ed.)* **1980**, *1*, 31–39.
150. Xue, W.; Huang, Y. Comparison of the DOB based control, a special kind of PID control and ADRC. In Proceedings of the 2011 American Control Conference, San Francisco, CA, USA, 29 June–1 July 2011; pp. 4373–4379.
151. Feng, H.; Guo, B.-Z. Active disturbance rejection control: Old and new results. *Annu. Rev. Control* **2017**, *44*, 238–248. https://doi.org/10.1016/j.arcontrol.2017.05.003.
152. Cui, K.; Li, R.; Polk, S.L.; Lin, Y.; Zhang, H.; Murphy, J.M.; Plemmons, R.J.; Chan, R.H. Superpixel-Based and Spatially Regularized Diffusion Learning for Unsupervised Hyperspectral Image Clustering. *IEEE Trans. Geosci. Remote Sens.* **2024**, *62*, 4405818.
153. Cui, K.; Tang, W.; Zhu, R.; Wang, M.; Larsen, G.D.; Pauca, V.P.; Alqahtani, S.; Yang, F.; Segurado, D.; Fine, P.; et al. Real-Time Localization and Bimodal Point Pattern Analysis of Palms Using UAV Imagery. *arXiv* **2024**, arXiv:2410.11124.
154. Cui, K.; Li, R.; Polk, S.L.; Murphy, J.M.; Plemmons, R.J.; Chan, R.H. Unsupervised Spatial-Spectral Hyperspectral Image Reconstruction and Clustering with Diffusion Geometry. In Proceedings of the 2022 12th Workshop on Hyperspectral Imaging and Signal Processing: Evolution in Remote Sensing (WHISPERS), Rome, Italy, 13–16 September 2022; pp. 1–5.
155. Shi, Y.; Zhang, C.; Liang, A.; Yuan, H. Fuzzy Control of the Spraying Medicine Control System. In *Computer and Computing Technologies in Agriculture, Volume II. CCTA 2007*; Li, D., Ed.; Springer: Boston, MA, USA, 2008; pp. 1087–1094.
156. Felizardo, K.R.; Mercaldi, H.V.; Oliveira, V.A.; Cruvinel, P.E. Modeling and Predictive Control of a Variable-Rate Spraying System. In Proceedings of the 2013 8th EUROSIM Congress on Modelling and Simulation (EUROSIM), Cardiff, UK, 10–13 September 2013; pp. 202–207.
157. Guzmán, J.L.; Rodríguez, F.; Sánchez-Hermosilla, J.; Berenguel, M. Robust Pressure Control in a Mobile Robot for Spraying Tasks. *Trans. ASABE* **2008**, *51*, 715–727. https://doi.org/10.13031/2013.24369.
158. Wang, R.-F.; Su, W.-H. The Application of Deep Learning in the Whole Potato Production Chain: A Comprehensive Review. *Agriculture* **2024**, *14*, 1225. https://doi.org/10.3390/agriculture14081225.
159. Zhao, C.-T.; Wang, R.-F.; Tu, Y.-H.; Pang, X.-X.; Su, W.-H. Automatic Lettuce Weed Detection and Classification Based on Optimized Convolutional Neural Networks for Robotic Weed Control. *Agronomy* **2024**, *14*, 2838. https://doi.org/10.3390/agronomy14122838.
160. Zhang, Q.; Su, W.-H. Real-Time Recognition and Localization of Apples for Robotic Picking Based on Structural Light and Deep Learning. *Smart Cities* **2023**, *6*, 3393–3410. https://doi.org/10.3390/smartcities6060150.
161. Li, Z.-H.; Cui, J.-X.; Lu, H.-P.; Zhou, F.; Diao, Y.-L.; Li, Z.-X. Prediction Model of Measurement Errors in Current Transformers Based on Deep Learning. *Rev. Sci. Instrum.* 2024, *95*, 4.
162. Li, Z.; Cui, J.; Chen, H.; Lu, H.; Zhou, F.; Rocha, P.R.F.; Yang, C. Research Progress of All-Fiber Optic Current Transformers in Novel Power Systems: A Review. *Microw. Opt. Technol. Lett.* 2025, *67*, e70061.