

Review

Electrification and Smartification for Modern Tractors: A Review of Algorithms and Techniques

Chaoxian Zhang ¹, Jun Li ^{1,2} , Chuxi Li ¹, Peihan Lin ¹, Linlin Shi ^{1,2}  and Boyi Xiao ^{1,2,*} 

¹ College of Engineering, South China Agricultural University, Guangzhou 510642, China; 20233173067@stu.scau.edu.cn (C.Z.); autojunli@scau.edu.cn (J.L.); 20243175003@stu.scau.edu.cn (C.L.); lan_bo097@stu.scau.edu.cn (P.L.); lynnshi@scau.edu.cn (L.S.)

² Guangdong Laboratory for Lingnan Modern Agriculture, Guangzhou 510640, China

* Correspondence: boyi.xiao@scau.edu.cn; Tel.: +86-130-0688-8652

Abstract

Agricultural tractors account for a substantial portion of greenhouse gas emissions in the farming sector, necessitating the development of sustainable machinery solutions. This study systematically reviews the latest advancements in electrification and smartification technologies for modern tractors, with a particular focus on algorithmic control strategies and their applications. Architecturally, the study provides a comparative analysis of four key configurations, pure electric, series hybrid, parallel hybrid, and series-parallel hybrid, detailing their respective advantages and challenges in energy efficiency and operational performance. From an algorithmic perspective, three primary methodologies—rule-based control strategies, optimization algorithms, and reinforcement learning—are examined for their applicability in energy management and control systems. The research further explores the integration of intelligent systems in unmanned farming scenarios, addressing critical challenges such as adaptive path planning in unstructured environments and multi-machine collaborative operations. A case study on battery-electric tractors demonstrates practical advancements in battery technology and energy management systems. Lifecycle cost analysis confirms the long-term economic viability of electrification, while outlining a forward-looking technological roadmap for sustainable and intelligent agricultural machinery.



Academic Editor: Bruno Bernardi

Received: 13 July 2025

Revised: 10 September 2025

Accepted: 12 September 2025

Published: 14 September 2025

Citation: Zhang, C.; Li, J.; Li, C.; Lin, P.; Shi, L.; Xiao, B. Electrification and Smartification for Modern Tractors: A Review of Algorithms and Techniques. *Agriculture* **2025**, *15*, 1943. <https://doi.org/10.3390/agriculture15181943>

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

Keywords: electric tractors; electrification; optimization algorithms; energy management; unmanned farms

1. Introduction

Contemporary society confronts an unprecedented environmental crisis characterized by collapsing ecosystems, intensifying climate instability, and deteriorating living conditions—consequences directly attributable to unsustainable fossil fuel dependence. These carbon-intensive energy sources, while historically enabling industrialization, now drive severe pollution and resource depletion globally [1]. Projections indicating peak oil production by 2030 underscore the critical need for energy transition [2]. Within this context, agricultural tractors emerge as significant contributors to sectoral emissions due to their traditional reliance on fossil fuels [3]. Current policy landscapes further challenge conventional tractor investments while intensifying environmental pressures.

The agricultural sector's decarbonization consequently hinges on transforming tractor technologies [4,5]. Traditional models exhibit critical limitations: excessive energy consumption directly impacts crop health and operator well-being through emissions exposure,

while requiring a large amount of manual operation [6], which brings a lot of vibration shock and safety risks [7–10]. These operational and environmental constraints position modern tractor systems—integrating electrification, sensing technologies, and intelligent algorithms—as essential solutions for sustainable farming [11,12].

Electrification and smartization present transformative pathways for agricultural machinery. Battery electric tractors enable strategic synergy with renewable energy infrastructure, particularly benefiting regions with abundant wind/solar resources where facility agriculture development can leverage spatial advantages [13–15]. The technological evolution in history has demonstrated continuous innovation: Siemens (Siemens, Berlin, Germany) invented the world’s first electric tractor, which was driven by a monorail and designed for rotary tillage [16]. However, these tractors were limited by their tracks, restricting their operational range. Following advancements in battery technology in early years, battery electric tractors powered by batteries began to emerge in Europe, America, and Japan. The Electric Ox series, manufactured by Canada’s battery electric tractor company (Electric Tractor Company, Canada) [17], featured a rated power range of 4 to 5.8 kW and incorporated an energy system consisting of six lead-acid batteries. These tractors were equipped with dual motors to drive the wheels and the power take-off (PTO) shaft, utilizing transmissions, electronic differentials, and other drivetrains, along with regenerative braking functions for various operations such as mowing and sweeping. As we entered the 21st century, the rapid development of new energy technologies facilitated the application of range-extending technology [18], integrated power electronics, and intelligent algorithms in agricultural tractors. Tractors equipped with diesel generator set range extenders emerged, boasting rated power outputs of up to 225 kW, demonstrating improvements in fuel consumption and operational efficiency compared to similarly powered tractors utilizing power shift transmissions. Additionally, John Deere’s Gridcon (Deere & Company, Moline, IL, USA) [19] model tractor eliminated the cab, replacing the battery pack with power supply cables while incorporating intelligent features such as navigation, obstacle avoidance, and automated turning. Concept tractors focused on pure electric and autonomous driving, such as the Kubota X (Kubota Corporation, Osaka, Japan) [20], have also been introduced, powered by a combination of lithium batteries and solar panels. These tractors are equipped with GPS, radar, and other systems, allowing for autonomous movement in the field. With the integration of AI technology, they possess advanced information processing capabilities, enabling data sharing to adapt to diverse terrains and manage various crops. The development timeline of typical models of tractors is presented in Table 1.

Table 1. The agricultural tractor development history table.

Year	Name	Key Functions and Technical Features	Energy Type	Picture
1912	Siemens First Electric Tractor	Rail-powered, wheeled structure, driving rotary tiller operations, power 36.8 kW	Pure Electric (External Power)	
1973	GE Elec-Trak (General Electric Company, Schenectady, NY, USA) [21]	Lead-acid battery driven, permanent magnet DC motor, power 5.9–11 kW, for home lawn mowing	Pure Electric (External Power)	

Table 1. Cont.

Year	Name	Key Functions and Technical Features	Energy Type	Picture
1995	Electric Ox	Lead-acid battery powered, dual-motor independent drive (travel + PTO), supported regenerative braking	Pure Electric	
2017	John Deere SESAM (Deere & Company, Moline, IL, USA)	Lithium-ion battery (130 kWh $\times$ 2), pure electric drive, CVT, 2 h heavy-load operation	Pure Electric	
2022	Dongfanghong HB2204 (First Tractor Company Limited, Luoyang, Henan, China) [22]	Series-parallel hybrid, E-CVT, 85% localization rate	Hybrid (Strong Hybrid)	
2024	Wantu 2604ET (Wantu Group, Wuhu, Anhui, China) [22]	World's first 260 hp pure electric model, LFP battery (7000 cycles), supports battery swap/supercharging	Pure Electric	

The main content of this review is as follows: After a brief introduction in Section 1, Section 2 will present the basic structure of agricultural tractors. Section 3 reviews and categorizes the algorithms applied to agricultural tractors in recent years. Section 4 introduces the latest intelligent applications of unmanned farms. Section 5 estimates the life cost of electric tractors through case analysis in combination with the unmanned farm of South China Agricultural University. Finally, the article concludes with a forward-looking perspective on tractors, summarizing their shortcomings and proposing improvements.

2. Classification of Modern Tractor

2.1. Battery Electric Tractor

Electric tractors represent a clean power alternative to traditional internal combustion engine tractors, with their core system architecture based on the integrated collaboration of electric drive systems, energy storage systems, and electronic control systems. Typical battery electric tractors (BET) use rechargeable battery packs as their power source, which drive electric motors and regulate power output through power electronic devices.

The single-motor drive architecture developed by Gao 2009 [23] utilizes a belt drive to connect the motor to the transmission, effectively absorbing overload impacts while meeting rated power demands. However, this configuration does not decouple the power take-off (PTO) shaft from the drive motor, leading to strong interdependence between tillage efficiency and vehicle speed, which limits agronomic adaptability. To address this issue,

Xu 2021 [24] proposed a dual-motor independent drive system that enables decoupled control of traction and hydraulic power. Zhang 2023 [25] further developed three drive modes and optimized power coupling parameters (Figure 1), substantially improving endurance performance. Tong 2023 [26] contributed a theoretical allocation framework that fills a critical gap in energy management for dual-motor systems. Empirical studies show that this architecture reduces operational coupling losses by 30% compared to traditional single-motor systems.

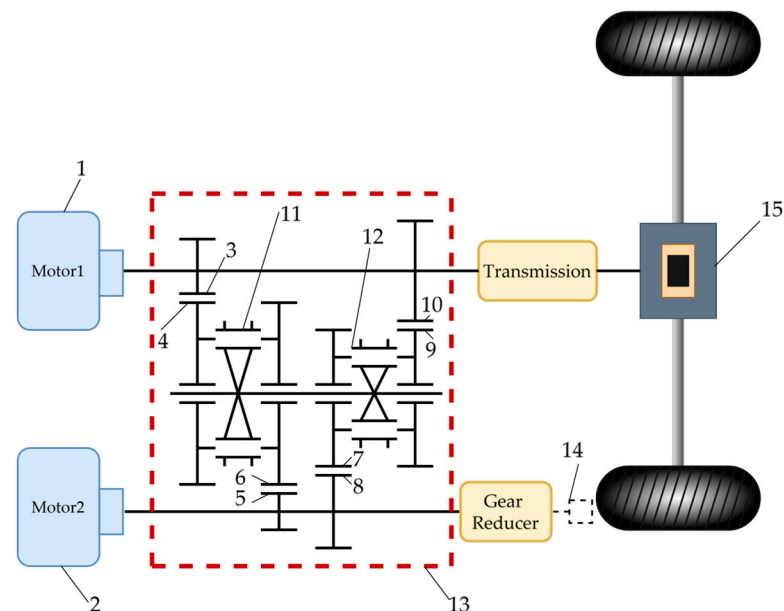


Figure 1. Dual-Motor tractor structure. 1. Traction motor; 2. PTO motor; 3~10. Transmission gear pair gear; 11. Synchronizer one; 12. Synchronizer two; 13. Power coupling device; 14. PTO; 15. Central transmission device.

In terms of performance, pure electric systems depend on battery capacity and motor peak power. Their fast-charging capability and battery-swapping mode [27] support continuous field operations. Zero-emission characteristics make BETs particularly suitable for greenhouse environments [28], while their low-torque vibration properties improve precision seeding uniformity.

However, BET technology still faces considerable challenges: battery range can drop by up to 40% during heavy-duty operations such as plowing [29], and sustained peak motor output leads to temperature rise, compelling the system to rely on power coupling mechanisms to maintain PTO output. As highlighted by Jiangyi H. [30], when loads exceed motor ratings, hybrid assistance must be triggered to ensure operational continuity. Many growers express concerns regarding long-term battery performance, safety, weight, and the potentially high and unpredictable costs of maintaining and replacing batteries as they degrade. Furthermore, extreme temperatures, humidity, and dust can adversely affect both battery and motor performance [31].

2.2. Hybrid Tractor

2.2.1. Series Hybrid Tractor

Series hybrid tractors are characterized by the engine driving a generator to produce electricity while operating within its optimal efficiency range [32]. Vehicle propulsion is entirely dependent on the electric motor, with the power take-off (PTO) function decoupled from wheel speed. A major advantage of this configuration is the ability to completely shut down the diesel engine when entering zero-emission zones. As illustrated in Figure 2, a

significant portion of the engine power in a series hybrid tractor directly drives the PTO shaft via the transmission, while the remaining energy is converted into electrical power. However, this rigid mechanical coupling locks the PTO shaft speed to the engine speed, significantly limiting adaptability across the operating range. Wang et al. addressed this limitation by introducing a dedicated motor for the PTO shaft, enabling more flexible speed control (see Figure 3 [33]).

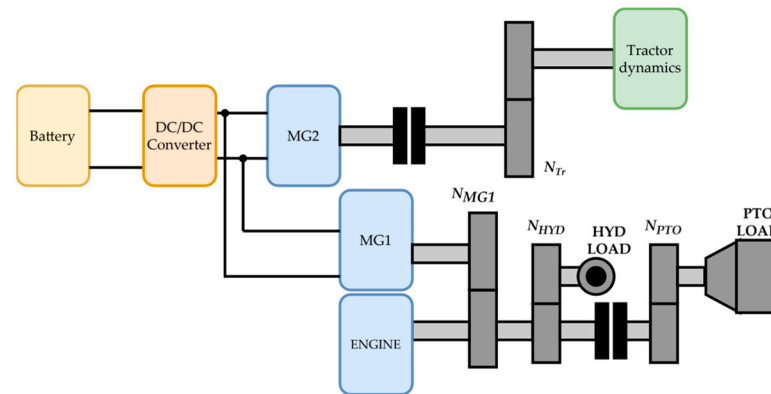


Figure 2. Series hybrid electric agricultural tractor configuration (S-HEAT) [34].

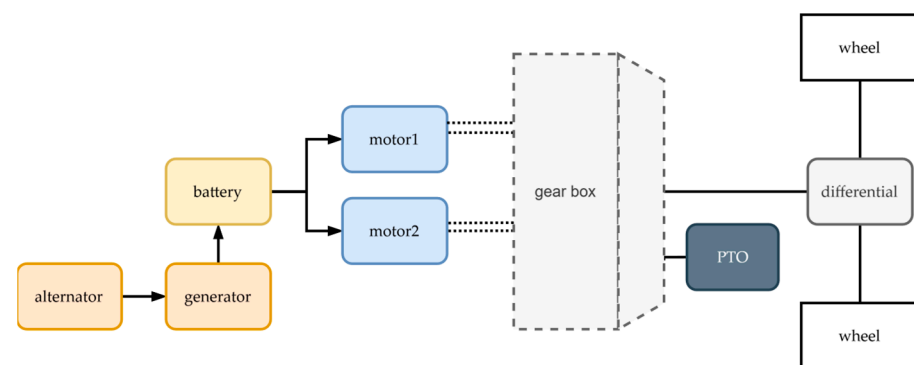


Figure 3. Range-extended battery electric tractor architecture.

Liu 2018 [35] developed a series hybrid tractor equipped with dual hub motors and implemented a three-stage energy management strategy based on load conditions. During high-load operations (e.g., plowing or heavy hauling), a dual-source generator-battery power supply mode is activated. For medium-load tasks (e.g., harvesting or light hauling), the generator directly powers the system. Under light-load conditions such as transport, the system operates in pure electric mode. Similarly, the Minsk tractor from Belarus (Minsk Tractor Works, Minsk, Belarus) [18] features a bidirectional energy storage system. Here, the generator is physically coupled to the diesel engine to form a generator set, which supplies all power converters through a DC link. This setup, combined with the electric motor, functions as an electromechanical continuously variable transmission (ECVT). Energy management focuses on optimizing power distribution between the generator set and the battery pack to minimize cost functions such as fuel consumption and emissions, while complying with dynamic, local, and global constraints [36]. A notable advantage is that electric drive enables continuous speed regulation independent of the internal combustion engine, allowing optimization of conversion efficiency in the engine and generator set. Additionally, minimum state-of-charge (SOC, a measure of the available battery capacity) windows (e.g., 30–70%) can be established to handle sudden load surges. Defining the battery's SOC min and SOC max as critical state variables helps delineate the system's operational safety boundaries [37].

Compared to pure electric tractors, the series architecture considerably extends operational range through continuous engine-driven power generation and reduces dependence on battery capacity. However, this is achieved at the expense of increased vehicle size, making the series hybrid more suitable for medium-to-large agricultural machinery applications. It is important to emphasize a fundamental distinction between series hybrid tractors and series hybrid electric vehicles: the latter benefit from brake energy recovery due to frequent acceleration-deceleration cycles. In contrast, tractors typically operate under low-speed, high-torque, steady-state conditions (e.g., plowing, rotary tilling), where opportunities for effective brake energy recovery are limited. As a result, tractors do not share the energy recovery advantages commonly seen in electric vehicles [38].

2.2.2. Parallel Hybrid Tractor

Unlike series systems, in a parallel hybrid architecture, part of the engine's power is used to drive the output shaft, while another portion is coupled with the electric motor to transmit power to the wheels. Intelligent regulation enables power superposition: the engine primarily responds to the wheel power demand, while the electric motor acts as a torque compensation module, dynamically supplementing the engine output. Under certain operating conditions, the engine and electric motor can also drive the vehicle independently. The electric drive path fully leverages the motor's inherent instantaneous torque capability to meet transient high torque demands, such as those required during starting. Additionally, the electric motor can operate in reverse as a generator, as illustrated in Figure 4.

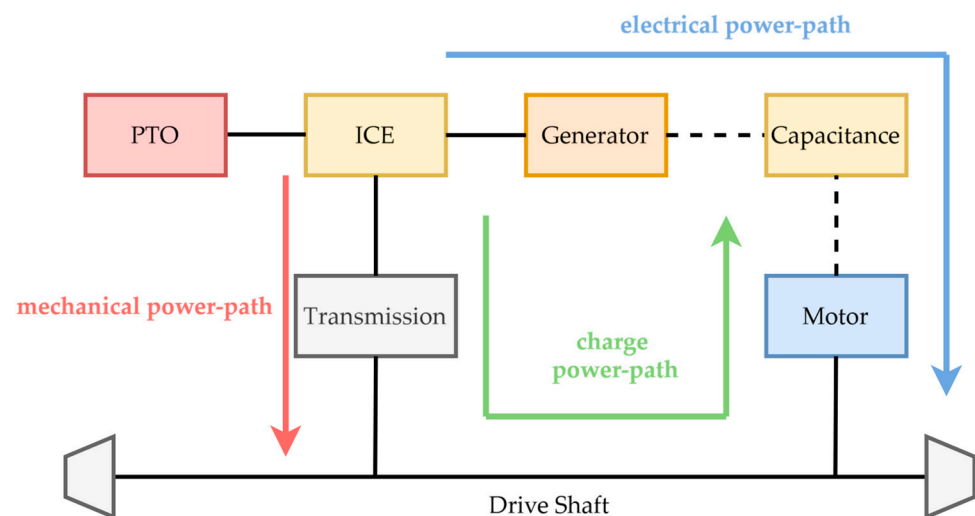


Figure 4. Parallel hybrid power transmission diagram.

The versatility of this architecture is evident across multiple applications. For example, Zhao et al. successfully integrated an electric motor with a turbocharged engine into a parallel hybrid tractor [39,40], which not only improved overall performance but also facilitated engine downsizing. Similarly, Kim et al. expanded power compensation possibilities using the same parallel architecture by developing a torque-assist strategy that calculates real-time electric drive compensation to maintain engine operation within its optimal efficiency range [41]. Building on this work, Lee 2017 [42] proposed three distinct control modes for parallel hybrid tractors: idle, power assist, and battery charging. Their system intelligently switches between these modes based on the relationship between engine speed and target speed, as well as the battery's state of charge. Subsequently, Zhu 2022 [43] further refined the control scheme by incorporating pure electric and regenerative braking modes. This extended system employs a hydraulic-mechanical continuously variable transmission

(CVT) to accommodate diverse operating conditions, such as tractor start-up and highway transport. Another parallel hybrid tractor designed by Deng 2012 [44] (see Figure 5) demonstrated improved driving force and hill-climbing performance under various conditions when the engine bore 60% and 40% of the load, respectively. By shifting gears as engine load increases, total energy consumption was reduced by up to 24% compared to conventional tractors. Concurrently, Francisco et al. addressed high fuel consumption in large engines by developing a novel parallel power architecture that combines a small diesel engine with an electric motor and a simplified electronic drive, delivering 54 kW rated power at 2300 rpm [45].

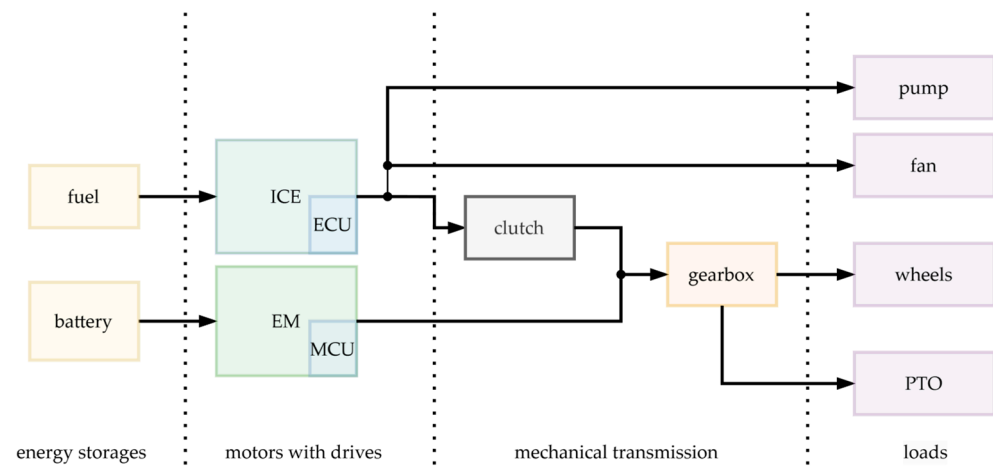


Figure 5. Diagram of parallel hybrid power transmission with PTO.

Overall, the adoption of a parallel hybrid architecture in agricultural tractors offers significant synergistic benefits: markedly enhanced traction, hill-climbing capability, and starting performance—particularly advantageous for vehicles requiring high engine power [38]. These established advantages and validated control strategies provide a solid foundation for future hybrid machinery development in the demanding field of agricultural engineering [40]. Limitations include restricted engine speed ranges, limited battery involvement in propulsion, and shallow discharge depths. These factors constrain the usable battery capacity, making it challenging to meet higher energy output demands [46].

2.2.3. Series-Parallel Hybrid Tractor

The series-parallel configuration effectively integrates the benefits of both series and parallel powertrains, as exemplified conceptually in Figure 6 by power-split e-CVT systems [47]. It comprises several key components: a planetary gear set for power splitting, two coaxial and concentrically arranged electric machines (MG/1 connected to the sun gear for speed regulation and MG/2 coupled to the ring gear for wheel propulsion), a diesel engine, and three electro-actuated clutches. The operational principle is fundamentally based on the kinematic relationships of the planetary gear set, where the speed ratio between the engine and wheels is dynamically controlled by adjusting the rotational speed of MG/1. This configuration enables power distribution through both mechanical (planet carrier–ring gear) and electrical (sun gear–MG/1–MG/2) paths. As illustrated in Figure 6, the system achieves multiple operational advantages including engine operating point optimization, pure electric driving capability, and power boost functionality through the generator/motor mode switching of MG/1. The integrated design allows for seamless transitions between different power flow configurations while maintaining compact packaging suitable for agricultural tractor applications.

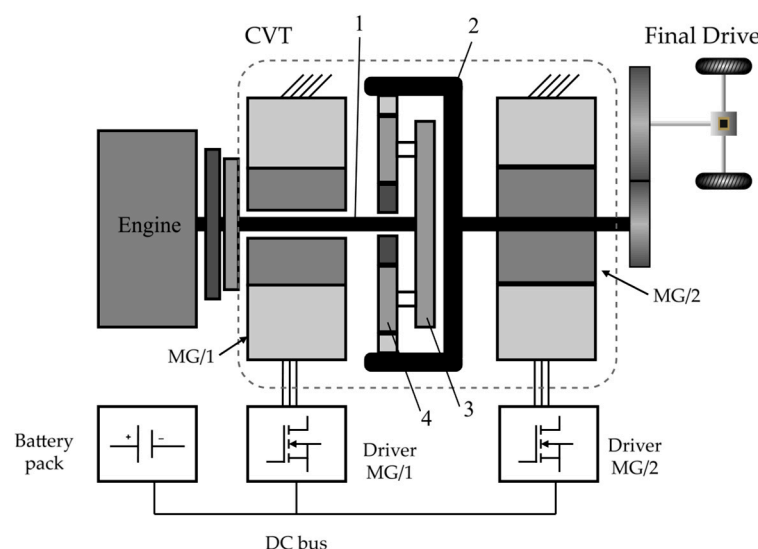


Figure 6. Series-parallel hybrid power transmission diagram. 1. Sun gear; 2. Ring Gear; 3. Planet carrier; 4. Planet Gear.

However, the operational demands of industrial and agricultural machinery present a fundamentally different set of challenges. Vehicles like wheeled front-end loaders and tractors face persistent extreme conditions: sustained low-speed operation under high torque, frequent idling periods, and specialized tasks demanding instantaneous power bursts and energy recovery opportunities (e.g., stationary charging). Standard e-CVT solutions like THS, optimized for broader automotive use, are not inherently tailored to excel under these unique and often severe constraints.

This requires the specialized design of robust and efficient architectures for these demanding environments. Sergio Grammatico [48] developed a novel series-parallel propulsion architecture for wheeled front-end loaders that prioritizes sustained engine operation within its peak efficiency range. A comparative analysis with THS shows that THS not only excels in automotive contexts but also aligns exceptionally well with the stringent energy management demands of industrial vehicles. This is a key metric for evaluating the advantages of series-parallel architectures, and it is thanks to Grammatico's architecture featuring active mode switching. Similarly, Fereydoon Diba et al. [49] modeled a parallel-series hybrid system for tractors that can handle various agricultural tasks. Strategically placing the electric motor between the clutch and transmission enables critical farm functions, such as braking energy recovery and fixed charging. These functions are essential for tractor efficiency, yet they are challenging due to structural complexity and stringent control algorithm requirements [50].

The comparison of tractors of different energy types is presented in Table 2.

Table 2. Technical comparison of modern tractor architectures.

	Power Source	Key Advantages	Main Challenges	Typical Applications
Electric Tractor	Battery + Single/ Dual Motors	- Zero emissions, simple structure [51] - Dual-motor design decouples traction and PTO systems [25]	- Limited range [52] - Poor adaptability under heavy loads [53]	Short-haul/fixed-site operations [26]

Table 2. Cont.

	Power Source	Key Advantages	Main Challenges	Typical Applications
Series Hybrid	ICE + Generator + Battery + Motor [34]	- Extended range (generator support) [54] - PTO speed independent of vehicle speed due to decoupling [54] - Optimized ICE efficiency [54]	- Large battery size/cost - Low braking energy recovery efficiency [55]	Medium/large-scale continuous fieldwork [48,55]
Parallel Hybrid	ICE + Motor (parallel coupling)	- Engine-motor torque assist [39] - Fuel mode backup [41] - Up to 24% energy savings (Deng [44])	- Complex control algorithms [41] - Higher fuel consumption in heavy tasks [45]	Variable-load scenarios (transport/plowing) [48]
Series-Parallel Hybrid	ICE + Dual Motors (planetary gear) [47]	- Optimal power split for efficiency [48] - Multi-mode operation [49] (electric/mechanical)	- High system complexity [47]	Complex operations (e.g., heavy loaders) [48]

3. Algorithms and Control System

In complex field operating conditions, tractors encounter multiple challenges including variable soil resistivity and uneven terrain, which result in several core operational issues: inconsistent plowing depth, significant fluctuations in drive wheel slip rates, reduced traction efficiency, and compromised path tracking accuracy [56]. Conventional control methods often fail to achieve multi-objective optimization under dynamically changing tillage conditions, particularly for electric and hybrid tractors that must simultaneously manage battery energy allocation, power distribution, and operational performance. This highlights the critical need to implement advanced intelligent control algorithms capable of precise coordination among key parameters—such as tillage depth, slip rate, traction force, and travel speed—to enhance both adaptability and operational efficiency in diverse agricultural environments [57].

As battery electric tractors and hybrid tractors differ in configuration, this difference leads to distinctions in their control objectives. For Battery electric tractors, the control strategy often focuses on optimizing battery energy utilization and load demand serving as foundational elements, while battery protection and energy efficiency remain central concerns. In contrast, hybrid tractors are employed in scenarios suitable for long-duration, high-power operations, where a balance between fuel and electricity consumption is essential. This involves the coordinated control of internal combustion engines and electric motors, placing greater emphasis on optimizing power source coordination. Current research [58] generally categorizes energy management strategies into three major types: rule-based energy management strategies, optimization-based energy management strategies, and deep learning-based energy management strategies, shown in Figure 7.

3.1. Rule-Based Algorithm

Rule-based algorithms primarily depend on a set of rules and strategies that are pre-established based on prior studies of vehicle behavior, motion laws, and empirical experience. The advantage of this algorithm lies in its simplicity, ease of implementation, and straightforward understanding and debugging.

During its early development and in applications with relatively stable operating conditions (such as constant-depth plowing and transport on flat terrain), rule-based strategies

relying on simple threshold values were widely adopted due to their straightforward logic and high reliability, laying the foundation for subsequent research [59].

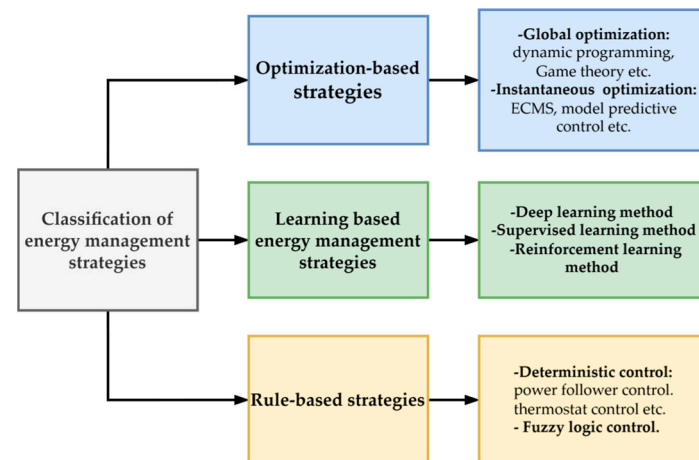


Figure 7. Classification of energy management strategies.

As application requirements grow increasingly complex, rule-based algorithms themselves continue to evolve. To achieve comprehensive optimization across multiple performance metrics—such as cost efficiency, traction efficiency, and emissions—rule-based strategies began evolving toward dynamic adjustments that encompass multiple objectives and variables. The primary direction of this evolution involves integrating with other control methods to form more intelligent rule systems, though their core principle of rule-based decision-making remains unchanged.

Commonly utilized control strategies in fuzzy logic determine the corresponding torque output of the motor and engine based on parameters such as the battery's SOC, accelerator or brake pedal position, torque demand, and vehicle speed, following specific rules to meet various driving requirements [60]. Wang 2020 [61] utilized three parameters—throttle, gear, and vehicle speed (plowing depth)—for comprehensive control. It can be adaptively adjusted according to the work and demonstrates good economic performance under farm transfer conditions. Fuzzy logic can integrate multiple input parameters and, according to established rules, generate various fuzzy rules to output the distribution coefficient of motor torque. Consequently, rule-based control strategies began to evolve towards dynamic adjustments that encompass multiple objectives and variables.

Building on this evolution towards greater complexity, subsequent research explored diverse applications of advanced rule-based methods. Xu et al. pioneered the application of fuzzy control to torque distribution within the electric drive systems of range-extended four-wheel-drive battery electric tractors, successfully enabling precise wheel slip regulation and intelligent torque allocation [62]. Jia et al. subsequently shifted focus to the global energy management perspective, demonstrating through comparisons the inherent energy-saving potential of optimized strategies over traditional rule-based approaches for range-extended structures [63]. Research expanded into system dynamics with Huang, who developed an adaptive fuzzy neural network to regulate compensation torque in real-time for dual-motor coupled drive systems, thereby enhancing response speed and robustness [64]. Concurrently, Ghobadpour tackled the challenge of variable external factors (farm conditions, weather, driver behavior) by designing a multimodal fuzzy logic controller, effectively ensuring optimal operation of the battery and range extender while preventing operational inefficiencies [65]. The scope of fuzzy control further broadened, as another study by Xu et al. applied it to multi-battery pack hybrid architectures, demonstrating its efficacy in suppressing battery power fluctuations and boosting system economy [66]. Engine

optimization also benefited from these techniques, Xu et al. employed a three-output fuzzy PID controller to select three efficient operating speed points for a series hybrid tractor—corresponding to power demands of below 25 kW, between 25 and 33 kW, over 33 kW—thereby achieving more targeted optimization of engine efficiency, as depicted in Figure 8 [67]. Li applied PID control to regulate plowing depth [68]. In response to the problem of uneven depth adjustment under significant environmental variations during field operations, which often limits the performance of traditional fuzzy PID control, he integrated three control strategies. This approach achieved precise plowing depth regulation while also improving slip rate, thereby effectively compensating for uncertainties in field conditions [56]. Finally, research continued on core rule-based strategies themselves, exemplified by Jia’s comparative study of Thermostat Control and Power Following Control (PFC) for tandem tractors, which revealed PFC’s advantages in fuel savings and reduced emissions (NO_x , CO) despite generating more particulate matter [69].

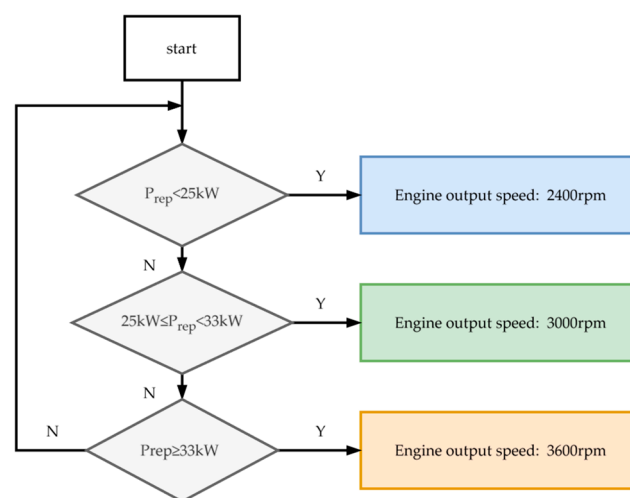


Figure 8. Fuzzy rules.

Nevertheless, the overall flexibility of rule-based algorithms—whether in their basic or optimized forms—remains constrained by their predefined rules. In the contemporary context focused on optimizing energy consumption and enhancing efficiency, these algorithms struggle to perform fundamental real-time adjustments during operation. This limitation restricts their application in highly complex, dynamic agricultural environments, making them more suitable for relatively simple farming scenarios or as benchmarks and supplements to higher-level optimization algorithms.

3.2. Optimization-Based Algorithm

Rule-based algorithms exhibit inflexible monolithic coupling in hybrid tractor energy distribution, inherently constraining integrated control. Optimization-based algorithms overcome these limitations by simultaneously achieving multi-objective optimization while dynamically responding to complex operating conditions through continuous feedback adaptation. A typical example is shown in Figure 9.

The evolution of Equivalent Consumption Minimization Strategy exhibits a clear trajectory from foundational calibration to predictive intelligence. Initial efforts by Hai Shi Duo et al. focused on redesigning equivalence factors to modulate engine torque, empowering motors to manage high-frequency load fluctuations [70]. Building on this, offline genetic algorithm refinement of equivalence factors demonstrated measurable fuel consumption reductions during rotary tiller operations through optimized power distribution [71]. The framework subsequently evolved towards dynamic responsiveness

with real-time equivalence factor adaptation driven by transient operating conditions [70], culminating in predictive SOC that enabled contextually precise adaptive control [72].

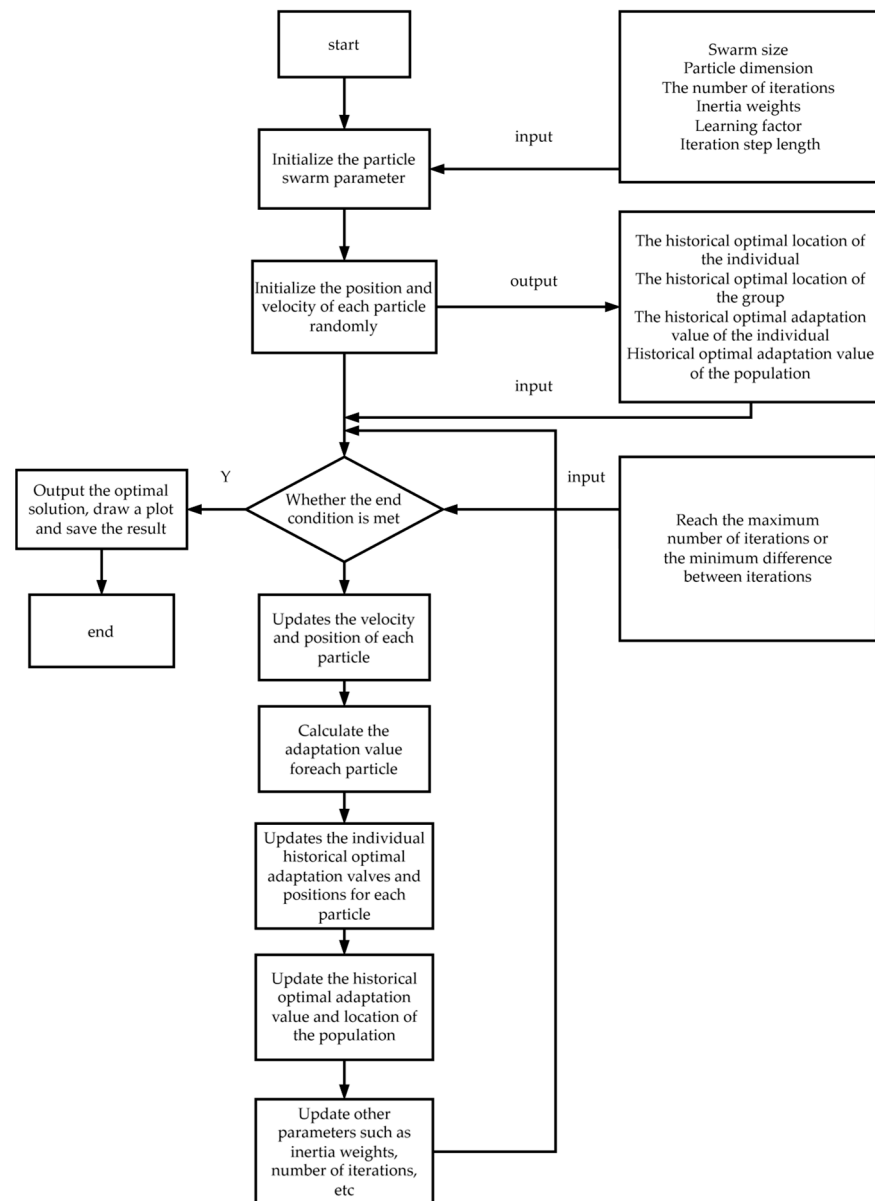


Figure 9. Example of optimization-based algorithm.

The parallel advances of diversified optimization methodologies have yielded significant progress in tractor energy management. Zhang 2023 [73] established instantaneous fuel minimization strategies using torque control variables and battery state variables, through rational control of diesel engine operating states. During rotary tillage and plowing conditions, equivalent fuel consumption was reduced by 4.7–6.3% compared with traditional power following strategy, while Radrizzani 2024 [74] enhanced ECMS functionality through speed-constrained energy management systems. ECMS converts electrical energy consumption into virtual fuel consumption via equivalent factors, enabling real-time coordination of torque distribution between the engine and electric motor. This proves critical for managing sudden high traction resistance during plowing. The algorithm commands the electric motor to rapidly provide auxiliary torque, preventing the engine from dropping into inefficient RPM ranges. This stabilizes operational efficiency while conserving fuel. Both methodologies are fundamentally based on the Equivalent Consump-

tion Minimization Strategy (ECMS) framework, which unifies fuel and electrical energy optimization through the core equivalence principle:

$$P_{eq}(t) = P_f(t) + \lambda \cdot P_b(t), \quad (1)$$

where $P_{eq}(t)$ is the equivalent power consumption, $P_f(t)$ represents fuel power (always positive), $P_b(t)$ denotes bidirectional battery power and λ dynamically balances these energy domains based on real-time operating conditions.

Model Predictive Control (MPC), an advanced control strategy that utilizes a dynamic model to predict future system behavior over a finite horizon and optimizes control inputs accordingly, is well-suited for agricultural terrain due to its predictive and rolling optimization capabilities. By integrating field maps or real-time sensors, MPC anticipates slope changes ahead [75]. This enables proactive power management: increasing torque before ascents to maintain power and preparing for energy recovery before descents to maximize efficiency. Further expanding methodological frontiers, MPC leverages mathematical models for quantitative forecasting by establishing robust energy-physical model coupling: Curiel-Olivares implemented a four-objective EMS with secondary target integration (battery degradation/temperature) [34,76], while hierarchical Haar wavelet decoupling reduced hydrogen consumption [77] and DOU et al.'s frequency-domain torque allocation suppressed engine oscillation amplitudes [78]. This framework enables multi-constrained dynamic equilibrium, supporting multidimensional expansions including ant colony algorithms and PMP (Pontryagin Minimum Principle)-ECMS.

Swarm intelligence's ability to rapidly locate satisfactory solutions within complex, multi-parameter spaces suitable terrain for tractor operation, with Wang optimizing unmanned tractor paths via a Harmony Search-enhanced Ant Colony method that dynamically adjusts evaporation factors using Sigmoid functions—boosting global exploration initially while accelerating convergence later [79]. Optimal control theory concurrently evolved: Zhang et al. applied Pontryagin's principle to maintain diesel/electric motors in high-efficiency zones, reducing field operation fuel consumption by 10.44–11.20% [80]; Yang et al. unified instantaneous and equivalent fuel consumption for 6% energy savings under NEDC cycles [81].

Efficiency-driven innovations proliferated: Cheng 2017 [82] utilized an enhanced Particle Swarm Optimization (PSO) algorithm to optimize the PID parameters for slip control. The optimal slip ratio parameters varied significantly across different terrain conditions, including asphalt with varying moisture levels, wet cobblestone, and snow-covered surfaces. The proposed PSO algorithm efficiently identified suitable parameter sets adapted to specific soil conditions within three seconds, enabling the drive system to achieve maximum traction performance, while Li 2024 integrated Variational Mode Decomposition to determine optimal parameter combinations to determine optimal power allocation between two motors across different operating conditions (plowing and transport) for peak efficiency [83]. Xu 2023 later optimized fuzzy PID controllers via Adaptive PSO with cosine-adjusted particle velocities, avoiding local optima [67]—demonstrating PSO's versatile compatibility, evidenced by Zheng 2022 enhancing diesel combustion chambers via neural network-guided inertia factor adjustment [84]. Complementary developments included Sun et al.'s wavelet-MOPSO vibration reconstruction [85] and TOPSIS-integrated PSO of Organic Rankine Cycles [86].

The following sections will discuss and summarize several types of algorithms that have been extensively researched and applied.

3.2.1. DP (Dynamic Programming) Algorithm

Dynamic programming (DP) derives globally optimal energy management strategies for fuel or electricity consumption by breaking down multi-stage decision problems into Bellman recursive equations. This approach is particularly suitable for tractors operating in fixed-field environments—such as during rotary tillage or ploughing—where load profiles exhibit strong cyclical and predictable patterns. Representative duty cycles (e.g., load variations across a single field pass) can be obtained in advance through measurement or simulation. Although the method’s strong dependence on a priori information limits its real-time applicability, this very constraint has motivated hybrid approaches that combine offline DP with online adaptive strategies. Li et al.’s offline stochastic DP tables combined with online extremum-seeking local optimization [87], Sheng et al.’s LSTM-powered rolling horizon current modulation for lithium-supercapacitor systems [88], Zhao’s field-validated DP-MPC fuel reduction [89], and Zhang et al.’s multi-DOF ECVT torque-distribution breakthrough [90] collectively demonstrate DP’s evolution into an offline-enhanced framework indispensable for MPC or extremum-seeking augmentation.

Therefore, the value of DP lies in its provision of a performance bound. The fuel economy of any online energy management strategy applied to tractors can be compared against the solution derived from DP, thereby enabling an objective assessment of the strategy’s merits.

3.2.2. Genetic Algorithm

Genetic algorithms (GAs) iteratively evolve encoded solution populations through natural selection, refining approximations generation by generation (Figure 10). Owing to their strong global search ability and polynomial time complexity, GA is well-suited to tackling multi-variable, multi-constrained optimization problems in tractor systems—such as balancing economic and power objectives—which are often challenging for conventional methods [91,92]. Xie et al. pioneered grouped elite retention [93], dynamically partitioning populations via Sigmoid adaptation for path planning. Concurrently, Li et al.’s nonlinear programming hybrid (NLPGA) merged gradient methods with genetic operators, demonstrating 23% faster convergence and 17% superior solution quality versus conventional GA—proving particularly potent for series hybrid tractors where engine-speed decoupling enables operating-point stabilization (9–12% fuel reduction via constant-RPM optimization) [91,92,94].

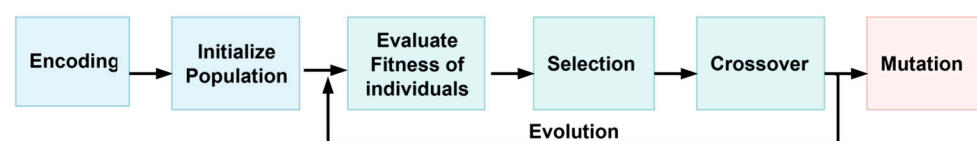


Figure 10. The process of genetic algorithm.

Cross-domain innovations propelled GA sophistication, when Zhou et al. bridged GA with model predictive control [95], real-time vehicle dynamics (speed/attitude/road conditions) optimized time-domain parameters, achieving adaptive MPC with 31% faster response and 0.82° tracking accuracy gains; this real-time paradigm subsequently extended to steering systems—Wang et al. [96] engineered MPGA-enhanced Stanley controllers reducing tractor path deviation by 37%. Chen et al. then refined navigation through Pareto-optimal control-point selection compressing planned path area by 28% while boosting positioning precision [97], while Yang et al. revolutionized load-spectrum extrapolation via threshold-optimized genetic reconstruction achieving 92.4% accuracy in three-point hitch traction modeling [98].

Quantum integration triggered a paradigm shift, Improved Quantum GA [99] leveraged quantum rotation gates and catastrophe operators to optimize weight matrices, accelerating convergence by 40% while preserving diversity—outperforming LQR, PSO, and QGA. Maturation manifested in drivetrain breakthroughs: Transmission optimization employing lifecycle speed-utilization models densified gear ratios within operational ranges [100], while Yang et al.’s NSGA-II implementation conducted multi-objective gear train optimization using elite-strategy non-dominated sorting, significantly reducing gearbox mass while enhancing fatigue strength with demonstrably superior outcomes over empirical methods [101].

Collectively, these advances crystallize GA’s role in conquering discontinuous/nonlinear challenges through four evolutionary vectors: grouped parallelism (GGABE), nonlinear hybridization, real-time adaptability (MPC/MPGA), and multi-objective refinement (NSGA-II).

3.2.3. Reinforcement Learning Algorithm

Reinforcement Learning (RL) mathematically models environmental interactions through the Markov Decision Process (MDP) framework (see Figures 11 and 12). In field operation environments, the fundamental RL mechanism operates as a closed-loop process: the system constructs state representations based on operational parameters such as power demand and battery state of charge (SOC). The agent then selects corresponding engine output actions based on the current state. After action execution, the environment returns feedback including SOC variation and energy consumption, which is converted into reward signals through composite metrics incorporating fuel consumption and SOC constraints. This reward is used to continuously update the control policy, forming a cyclic optimization process: “State → Action → Environmental Feedback → Reward → Policy Update” [102]. This theoretical framework demonstrates strong explanatory utility in agricultural powertrain optimization—Dou Haishi et al.’s team pioneered its validation by constructing an MDP state-transition model for traction power using operational parameters from tillage operations [103]. This methodological paradigm extends to new-energy vehicles, where fuzzy speed prediction strategies successfully resolve energy allocation challenges in fuel-cell heavy-duty trucks, demonstrating RL’s cross-domain adaptability in mobile powertrain systems [104]. Collectively, these studies reveal the core value of the MDP: its ability to decouple complex operational conditions into discrete decision sequences in dynamic environments.

At the methodological level, a persistent bifurcation evolves along dual pathways: model-based RL relies on environmental dynamics modeling (state transition probabilities/reward functions), whereas model-free variants directly optimize policies from interaction data. This divergence fundamentally manifests inherent tradeoffs between prediction accuracy and computational efficiency—the former offers strategic foresight when dynamic knowledge is complete, while the latter exhibits superior robustness under systemic uncertainties.

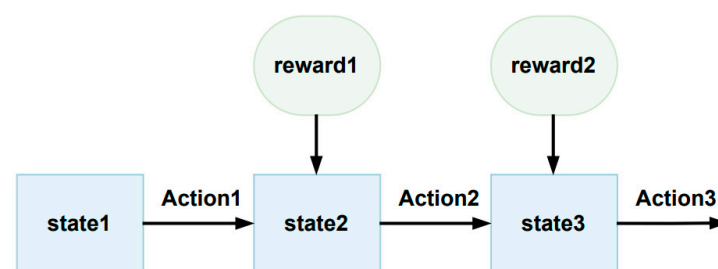


Figure 11. Markov decision process (MDP).

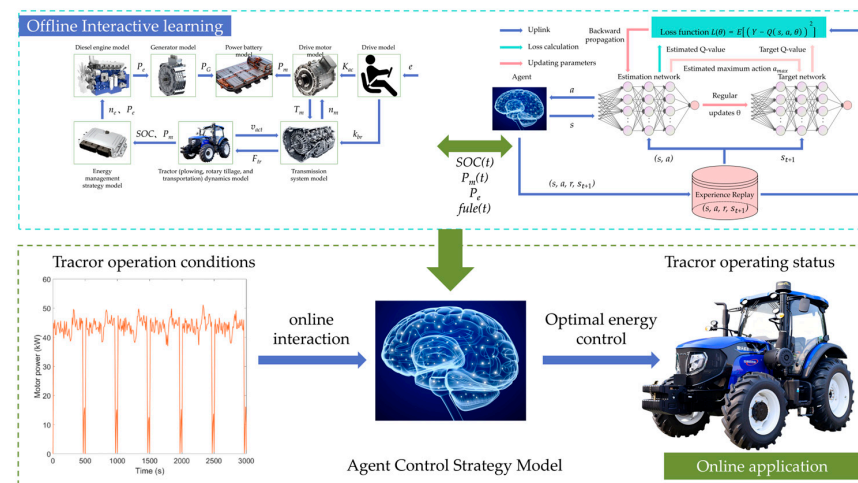


Figure 12. The process of reinforcement learning algorithm [102].

1. Value Function-based

Value-based reinforcement learning focuses on estimating state-action quality through value functions, with Q-Learning, SARSA, and DQN as primary approaches. While Q-learning's model-free nature enables parametric optimization [105], its inherent constraint of discrete action outputs impedes high-dimensional vehicle control. Foundational work by [106] pioneered fast Q-learning for hybrid tracked vehicles, optimizing throttle control to boost fuel economy—establishing efficacy despite discrete limitations. This dual reality of capability-constraint coexistence prompted iterative refinements: initial adaptations like reducing action dimensionality to six power options streamlined fuel-line optimization [107] yet sacrificed granularity; Han et al.'s double deep Q-learning [108] countered over-optimistic value projections; parametric Q-learning [109] validated transferable energy rules. Ultimately, Wang 2024's preview-enabled controller transcended foundational limits—suppressing wheel-loader path errors by 25–37.5% (positional) and 27.3–27.8% (heading) through dynamic state compensation [110], demonstrating domain-specific observers resolve Q-learning's core constraints.

2. Policy-based

Policy-based reinforcement learning overcomes the inherent limitations of value-function intermediation by directly optimizing decision policies, establishing core advantages in continuous action space applications. As a paradigmatic framework, the Actor-Critic architecture leverages synergistic mechanisms between policy-generation networks (Actor) and value-evaluation networks (Critic). This integration preserves the optimization essence of policy gradients while incorporating value-function guidance, thereby ensuring dual guarantees of exploration efficiency and policy stability. However, the framework remains constrained by sampling inefficiencies originating from policy gradients—manifesting as slow training convergence and policy oscillations in dynamic environments [111]. This fundamental limitation necessitates multidimensional innovations. Within algorithmic hybridization, the deep integration of multilayer neural networks with AC architectures constructs closed-loop optimization capabilities for agent behavior sequences, enabling prior studies [112] to resolve coupling decision challenges intractable to conventional systems. Xiao 2022's [113] team subsequently extended this paradigm to new-energy vehicle management, where the Safety-SAC algorithm innovatively mapped physical characteristics—charging rates, battery discharge curves, and fuel conversion efficiencies—into nonlinear reward functions. This approach substantially enhanced operational adaptability for hybrid powertrain control [113]. Concurrently, Elhaki et al.'s

neural adaptive controller overcame the dual challenges of unmeasurable velocities and actuator saturation in electric tractors, achieving high-precision torque control through dynamic identification of system uncertainties [112]. Parallel AGV energy-regulation research demonstrated the engineering value of Deep Deterministic Policy Gradients, reducing energy consumption by 4.6% via continuous action-space optimization of target velocities [114], collectively evidencing the framework’s efficacy in strongly nonlinear mechanical systems.

The proven real-time deployment ability of convergent reinforcement learning agents significantly reduced computational burdens for onboard controllers, as demonstrated in [115]. This fundamental capability subsequently enabled transformative architectural innovations: Lian’s team achieved a notable breakthrough in multi-physical control for logistic Policy Gradient (DDPG). In their proposed architecture, the Critic network assesses discrete action values, whereas the Actor network produces continuous commands for tractor engine power modulation. This hybrid approach enables tractors to adapt to subtle variations in soil resistance during ploughing operations, achieving smooth power adjustment and seamless transitions [116]. Parallel developments included Zhang et al.’s enhanced DDPG algorithm, which restructured policy-update mechanisms to optimize gradient utilization while preserving single-step update characteristics, ultimately elevating dual-motor system efficiency by 5% [117]. Tang’s pioneering work further advanced the field through a dual-agent architecture enabling parallel training of transmission shifting strategies (managed by a DQL agent) and energy management policies (handled by a DDPG agent), effectively eliminating the response delays inherent to sequential optimization approaches [118]. These collective breakthroughs, however, revealed critical vulnerabilities—particularly DDPG’s hypersensitivity to hyperparameters that frequently trapped optimization processes in local optima—which in turn catalyzed the emergence of Asynchronous Advantage Actor-Critic algorithms. The latter’s parallel sampling mechanisms achieved a 49% reduction in emissions compared to dynamic programming, as validated through pollution control applications [119].

To resolve slow parameter updates in Policy Gradients, Proximal Policy Optimization (PPO) employs trust-region clipping and adaptive learning rates. Empirical vehicle efficiency studies demonstrate that coordinated powertrain optimization can yield at least 29% energy savings [120], establishing a foundational efficiency benchmark. This catalyzed the integration of RL with Model Predictive Control, enhancing vehicular responsiveness while maintaining fuel economy [121]. Multi-step reinforcement learning refined energy efficiency via state-action chains [122], while Zhang et al.’s DDQN enabled agricultural machine optimization [123]. Hybrid energy systems further validated these synergies, attaining 4.31% energy reduction in untrained conditions [124]. Collectively, these advances confirm RL’s dynamic decision-making aptitude, despite persistent challenges in sample efficiency [125].

Recently, some new RL algorithms have emerged and gradually filled this gap, as presented in Table 3 below.

Table 3. The recently emerged reinforcement learning algorithms.

Algorithm	Core Advantage	Typical Application	Tractor Adaptability
DreamerV3 [126]	Cross-task zero-shot adaptation	Game AI, Robotics Simulation	Adaptive terrain navigation
R1-Searcher [127]	Dynamic retrieval-reasoning loop	Real-time QA, Customer Service	Fault diagnosis knowledge base
GRPO (Group Relative Policy Optimization) [128]	Value-function-free optimization	Math Reasoning, Code Generation	Low-power edge deployment

Table 3. Cont.

Algorithm	Core Advantage	Typical Application	Tractor Adaptability
HEPi (Heterogeneous Equivariant Policy) [129]	SE(3)-equivariant action space	Rigid/Deformable Object Manipulation	Precision implement control
ExpoComm [127,130]	Linear-communication-overhead topology	Large-scale Multi-Agent Systems	Swarm farming coordination

The algorithmic evolution in agricultural tractor energy management progresses from rigid rule-based methods toward adaptive AI-driven solutions. While conventional strategies offer operational simplicity, their inflexibility hinders dynamic performance optimization. Subsequent optimization techniques—including dynamic programming and genetic algorithms—demonstrate moderate yet consistent fuel efficiency gains through multi-objective calibration, though constrained by computational intensity. More significantly, reinforcement learning frameworks establish a paradigm shift, with hybrid architectures combining deep learning and model predictive control achieving substantial energy conservation across diverse field conditions.

Persisting challenges in computational efficiency and safety assurance necessitate focused innovations: streamlined edge-compatible algorithms to reduce latency, physics-embedded learning architectures to improve environmental adaptability, and standardized validation methodologies to bridge simulation-field gaps. These advancements collectively propel the development of autonomous systems integrating quantum-accelerated optimization with adaptive control, marking a critical transition toward energy-sustainable agricultural machinery.

4. The Intelligence of Unmanned Farms

A series of intelligent algorithm technologies are key initiatives for achieving smart agriculture, while unmanned farms represent an important direction for the future transformation and upgrading of agriculture. They will enable autonomous farming operations by agricultural machinery, reducing human labor more significantly than the intelligent agricultural machinery previously discussed (two typical work cases are shown in Figure 13). Agricultural unmanned machines utilize algorithms to achieve functions including agricultural machinery path tracking and planning, multi-machine collaborative communication control, and self-control in complex environments.



Figure 13. (a) Automatically accept crops; (b) Operate according to the planned route.

4.1. System Architecture

The architecture of unmanned farms is composed of the foundational layer, decision-making layer, and application service layer [131]. The primary system components for

enhancing the efficiency of unmanned farms involve controlling various hardware infrastructures from the intelligent decision-making cloud platform and then deploying multiple agricultural machines for coordinated operations. Automatically proceed to the target operation area [132], complete the mapping and route planning for the operation area, adaptively perform the operation independently or in multi-machine collaboration, transport crops back to the warehouse, and return to the charging station for recharging. Such static task assignments (fixed farming sequences) can be roughly divided into operation time and non-operation time, with non-operation time directly affecting operation efficiency. Currently, the focus is mainly on improper path planning, high costs of multi-machine collaborative assignment of operation fleets, and occurrences of uncertain situations [133].

4.2. Multi-Machine Collaboration

In agricultural automation systems, multi-machine collaboration fundamentally relies on coordinated operations between primary harvesters and auxiliary transport vehicles, where the auxiliary machines intelligently determine optimal cooperation timing and positioning by continuously monitoring the main harvester's operational status, thereby enabling dynamic adjustment of task sequences through real-time performance prediction. The theoretical foundation for such systems is established in [134], which specifically addresses collaborative path planning optimization through shortest-path algorithms in field conditions while developing an enhanced continuous-time Markov chain model for adaptive grain unloading sequence adjustment, providing critical mathematical frameworks that directly support practical implementations. Building upon these theoretical models, the study [135] advances the system through a Finite State Machine (FSM)-based cooperative strategy that systematically integrates four operational phases—harvesting, waiting, unloading, and transferring—leveraging high-precision BeiDou positioning (± 1 cm) and robust 4G/5G communication networks to achieve seamless coordination, with field validation under standardized conditions (120 m $\times$ 60 m test plot) demonstrating the system's capability to execute 28 harvesting passes at 0.8 m/s with 1.9 m cutting width while autonomously managing six grain transfer cycles, ultimately achieving 120 min of continuous unmanned operation at 0.35 hm²/h harvesting efficiency. Further enhancing these technological achievements, Zhang et al. [136] refine the system's precision through multi-sensor fusion, combining RTK-GNSS and IMU data with Kalman filtering algorithms and incorporating a Hammerstein model of the steering system to attain sub-centimeter parking alignment accuracy.

4.3. Path Tracking Control Technology

The automatic navigation system is the core of intelligent tractors for precise operation, and the path tracking control technology is the core technology of automatic navigation tractors, directly affecting the quality and efficiency of the operation. Current research faces challenges such as multi-source disturbance compensation in complex farmland environments and the improvement of unstructured path tracking accuracy.

Considering that in path planning, to avoid the impact of variable model parameters on agricultural machinery path tracking, PID methods are often used, employing model-independent heading deviation and lateral position deviation as feedback corrections with PD and Bang Bang control algorithms [137]. Further improvements [138] have been made by adopting the preview tracking dual-PID method, which has reduced the average absolute error from 5.12 to 2.23 cm (a 56% improvement) and the maximum deviation from 12.2 to 4.14 cm (a 66% improvement) compared to PD path tracking. Fan et al. [139] switched to single-neuron PID control on curved road sections. Affected by the smoothness of the sampling path, Zhang et al.'s path tracking method based on B-spline curve optimiza-

tion [140] reduces the tracking error by 38% compared to traditional methods in hilly terrain with curvature changes up to 0.25 m^{-1} , by fitting the path curvature with cubic B-splines. Subsequently, He et al. [141] further explored the potential for broader applications of unmanned agricultural machinery in complex and variable curved-edge operations on irregular farmland, using a third-order full-state feedback controller with lateral deviation, heading deviation, and heading increment as the state vector. The introduction of the tire-ground interaction model became a research hotspot, followed by [142] proposing lateral control compensation, enabling rapid deviation correction and enhanced stability control in rugged terrain. Path planning has evolved from the traditional pure pursuit algorithm, which relies on a fixed look-ahead distance, to incorporating complex curve compensation in dynamics (such as side-slip compensation and B-spline optimization), significantly enhancing tracking accuracy and anti-interference capability under complex path conditions.

4.4. Automatic Navigation System

The agricultural machinery autonomous navigation system significantly enhances positioning and control accuracy in complex environments through the integration of multiple technologies. He et al. [143] established the coordinate system transformation relationship and fused data using Kalman filtering to indirectly obtain the central posture of the rice transplanter, taking the transplanting point as the navigation control point, shifting the control from the “center of the machine body” to the “working device control,” laying the foundation for high-precision navigation in complex environments such as paddy fields. Subsequently [144] he incorporated the agricultural machinery posture (roll/pitch angle) into the MPC state variables for the first time, suppressing the interference of paddy field side slip and trajectory deviation in the slippery paddy field environment through posture correction, promoting the evolution of navigation control from the “ideal road model” to the “unstructured farmland model.” Hu et al. [145] developed a low rolling path planning algorithm specifically for the harvesting of ratoon rice, employing the traditional ant colony algorithm and the 2-opt algorithm to obtain the optimal turning strategy. This approach transforms the problem of path planning for unloading grain during ratoon rice harvesting into a vehicle routing problem with capacity constraints, thereby ensuring the secondary growth of ratoon rice. The measurement of steering wheel angle directly affects the precision of autonomous driving control and operational effectiveness. Zhang et al. [146] determined the relationship with the steering wheel angle of the tractor using an angle sensor and applied a steering wheel angle zero deviation estimation method based on the least squares principle. He et al. [147] improved dynamic response based on the nested PID steering control algorithm, with steering angle control error less than 2° . A tractor steering angle estimation method without front wheel sensors combines the ARMAX(Autoregressive Moving Average with Extra Input) model with Kalman filter (KF) and introduces a speed compensation mechanism. Multi-sensor fusion technology, particularly in enhancing the navigation control accuracy and robustness of autonomous agricultural machinery, has been widely recognized as the core guarantee for improving the reliability of autonomous driving systems in complex field environments.

4.5. Commercial Applications (JD Link System)

John Deere’s JD Link system [148] exemplifies a practical commercial application. This integrated hardware, software, and cloud-service solution features revolutionary real-time data synchronization across all agricultural machinery (see Figure 14). It utilizes Starlink dual-mode terminals to ensure transmission rates $\geq 187 \text{ Kbps}$ even in remote areas. With real-time monitoring from over 200 sensor nodes, JD Link enables a predictive mainte-

nance system leveraging a global fault database encompassing over 15,000 failure modes, establishing a comprehensive framework for intelligent agricultural machinery's fully digital ecosystem. The next-generation system will incorporate an edge computing architecture deploying lightweight AI models directly on equipment. This advancement means future tractors will not only transmit data but also perform real-time autonomous decision-making: instantaneously adjusting spray valves upon weed identification or dynamically optimizing tillage depth based on soil compaction measurements.

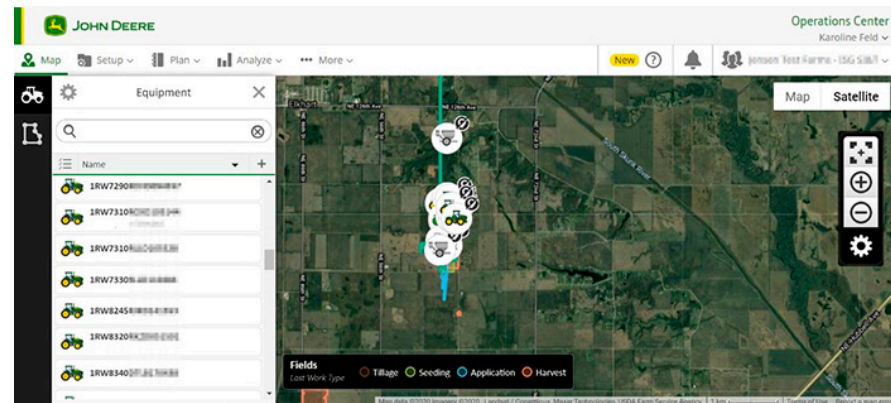


Figure 14. View the device intuitively on the map through the device.

4.6. Edge Intelligence and Future Directions

The intelligent of unmanned farms evolves from the basic control of a single agricultural machine (such as straight-line tracking) to the collaborative optimization of multiple machines, adaptation to complex environments, and then to farm-level intelligent decision-making, forming a closed loop of “execution to collaboration to adaptation to decision-making.” This will propel unmanned farms from partial automation towards comprehensive intelligent development [149].

Despite the rapid advancement of unmanned farm technologies, several critical challenges impede their widespread commercialization and reliable deployment. A primary concern is the vulnerability of high-precision GNSS positioning in challenging environments like dense crop canopies or mountainous terrain, where signal attenuation or blockage can cause navigation failures, necessitating robust multi-sensor fusion solutions 4. Furthermore, communication latency and unreliable connectivity in rural areas pose significant risks for synchronized multi-agent tasks, such as cooperative harvesting and transport, where even minor delays can lead to operational failures 5. The limited endurance of electric agricultural machinery complicates continuous fleet operations, requiring sophisticated energy-aware scheduling to manage charging cycles without creating bottlenecks 1. Additionally, the lack of unified data standards and software interoperability among machinery from different manufacturers creates data silos and hinders seamless integration into a cohesive farm management system, underscoring the urgent need for industry-wide adoption of common communication protocols.

5. A Case Analysis of an Electric Smart Tractor

The Fendt e100 Vario electric tractor (AGCO Corporation, Marktoberdorf, Bavaria, Germany), introduced in 2017 (show in Figure 15), features a 100 kWh, 650 V lithium-ion battery pack and an electric motor delivering 50 kW rated power with a peak output of 66 kW and 347 Nm torque. At its rated 50 kW power level, it achieves five hours of continuous operation. The tractor integrates CCS Type 2 fast-charging technology supporting up to 22 kW AC or 80 kW DC, enabling a 40 min charge to 80% capacity. A

collaboration with Blue World Technologies developed a methanol fuel cell range extender using high-temperature PEM technology to convert liquid methanol into hydrogen. This system doubled the operational range in laboratory and field tests while retaining diesel-like rapid refueling capabilities. The design offers three operational modes (ECO for maximum range, Dynamic for balanced performance, and Dynamic+ for peak output) alongside sophisticated battery management including seasonal temperature adjustments (preheating in winter, cooling in summer), user-configurable charging timers, and C-rate limitations to prevent thermal damage. Its transmission, adapted from the Vario 200 series, enables continuous traction across 0.02–40 km/h. The large-capacity battery supports bidirectional energy flow, allowing grid feedback of surplus power and enabling net-zero carbon operation when charged via on-farm renewable sources like biogas, solar, or wind energy. Fast-charging compatibility, extended range through methanol technology, adaptive driving modes, and intelligent thermal management collectively demonstrate this model's technical maturity in sustainable agricultural mechanization [150].



Figure 15. The Fendt e100 Vario electric tractor.

Experimental validation of total cost of ownership (TCO) was conducted on a 9333 m² test site configured for double-cropping rice production [151]. This controlled environment implemented full-cycle autonomous operations—land preparation, sowing, crop protection, and harvesting—across 32 standardized equipment passes (2 m working width). The infrastructure utilized precision agriculture technologies, achieving ± 2 cm positioning accuracy through integrated navigation systems. These operational parameters established the baseline for quantifying energy consumption patterns across sequential farming activities [152].

Dynamic cost assessment during four primary operations revealed that sowing requires the lowest operational speed, resulting in extended duration and maximal electricity consumption. Land preparation activities occurred twice per growing season, integrating both pre-planting rotary tillage and post-harvest straw management. Conversely, high-speed crop protection operations (e.g., pesticide application and irrigation) exhibited substantially reduced electricity requirements due to shorter operational durations.

To evaluate the operational costs of a typical tractor, a cost analysis is performed in Table 4. For the complete task described, the total electricity consumption is 294.88 kW·h over 9.72 h. According to relevant standards [153–155], the typical annual operating time for tractors is assumed to be 1200 h. Using the average electricity price in Guangzhou, China, of 0.1 USD/kWh [156]—noting that agricultural operations often occur in rural areas distant from urban centers and may benefit from localized subsidy schemes, potentially further reducing the effective electricity cost—the energy cost is calculated. Table 5 details the approximate investment costs associated with establishing a fully operational unmanned farm.

Table 4. Specific information on different types of operation.

Operation Type	Speed (km/h)	Time (min)	Average Annual Frequency (Time)	Annual Energy Consumption (kW·h)
Land Preparation	6	45	4	24.10
Sowing	3.5	85	2	40.80
Crop Protection	15	22	5	9.68
Harvesting	4	63	2	34.24

Table 5. Life cycle cost between electric tractor in unmanned farms and 44.1 kw diesel tractor (US \$).

Cost Category	The Range of 44.1 kw and 58.8 kw Electric Tractor (in Unmanned Farms)	44.1 kw Diesel Tractor
Energy Consumption	60,000–105,000	304,691.7
Maintenance cost	19,314.4–25,953.0	7518.4
Replacing cost	50,446.1–67,261.5	0
Cost of tractors (including tax)	35,767.4–48,061.0	12,045.7
Insurance	13,144.5–17,662.4	3070.0
residual value	15,018.5–20,180.6	3507.7
Total	163,653.9–243,757.3	323,818.1

It can be seen from the table that although the selling price, insurance, maintenance and replacement costs of electric tractors are all higher than those of traditional diesel tractors, even when compared with a 44.1 kw diesel tractor, the total annual energy consumption cost drops by nearly 70%, saving nearly 200,000 USD in annual energy costs [157]. The total cost is only 50–75% of that of diesel tractors. the electric tractor demonstrates significant advantages in energy expenditure. In the future, as the cost and scale of vehicle manufacturing expand and drive down other additional costs, the total cost will continue to decline. Labor costs are also substantially reduced, as operations require only 2–3 technical personnel and maintenance workers. From an environmental perspective, Proctor’s research found that the reduction in CO₂ emissions from micro electric tractors can reach 86–89% [158]. In conclusion, with anticipated future reductions in electricity costs and iterative upgrades in smart technologies leading to further declines in fixed costs, electric tractors present a highly suitable solution for large-scale farm adoption and exhibit strong competitive potential in the market.

6. Conclusions

This study provides a systematic review of the current progress in the electrification and intelligentization of agricultural machinery, with a focus on power management strategies ranging from pure electric and hybrid architectures to advanced algorithms such as deep reinforcement learning and model predictive control. Through an integrated analysis of electric motors, power take-off (PTO) systems, battery management systems, and holistic control strategies, this article summarizes the notable improvements achieved by existing technologies in fuel efficiency, operational stability, and algorithmic responsiveness. Based on this analysis, a projected technology roadmap for the coming years is outlined in Table 6.

Despite promising advances, the transition from laboratory research to large-scale industrial application still faces considerable challenges. Although electric and hybrid systems have demonstrated superior energy efficiency, reduced emissions, and improved maintainability—particularly in low-speed, high-torque, and precision task scenarios—their widespread adoption is hindered by limitations in battery energy density, insufficient driving range, and unsatisfactory economic performance under high-power conditions. In the domain of energy management, advanced control strategies such as ECMS, MPC, and

deep reinforcement learning show strong potential in simulation environments for optimizing power split and enhancing dynamic response. However, their real-world applicability is constrained by high computational demands, reliance on accurate pre-existing models, and a lack of sufficient field validation. Furthermore, while recent modeling efforts have improved the characterization of complex dynamics such as soil-implement interactions and terrain variations, most models are still developed under controlled laboratory conditions or small-scale trials. The absence of long-term, multi-regional, and cross-seasonal data impedes the development of accurate and adaptive machine-implement-soil coordination strategies. At the system level, although unmanned operations and swarm robotics open new avenues for intelligent farming, issues related to sensor robustness in harsh environments, communication reliability, and interoperability with conventional machinery remain unresolved.

Table 6. Future technology roadmap.

Phase	Timeframe	Technical Focus	Application Scenarios	Policy/Industry Recommendations
Short-term	2025–2030	High-energy LFP batteries; hybrid EMS (rule + optimization)	Protected horticulture, orchards; light-load operations	Purchase subsidies; energy/range standards;
Mid-term	2030–2035	Solid-state and hydrogen fuel cells; tractor–implement–soil coordination; edge–cloud decision-making	Hybrid tractors mainstream; wider use of pure electric; regional unmanned farm pilots	Agricultural big data platforms; interdisciplinary R&D; green supply chains
Long-term	Beyond 2035	AI-driven autonomous operation; closed-loop energy ecosystem	Tractors as Ag-IoT nodes; integrated energy–information flows	Build an integrated Agricultural IoT ecosystem; renewable energy–microgrid integration

Moving forward, the evolution of agricultural machinery will depend on advances in multi-energy integration (e.g., solid-state batteries and hydrogen fuel cells), modular powertrain design, lightweight and embedded algorithm implementation, big-data-driven dynamic modeling, and reliable low-power agricultural IoT networks. These developments are essential to achieve integrated and autonomous farm-level management systems, supporting the transition toward greener, more efficient, and intelligently autonomous agricultural machinery.

Author Contributions: Writing—original draft preparation, C.Z.; validation, J.L.; investigation, C.L.; data curation, P.L.; formal analysis, L.S.; Supervision and Editing, B.X. All authors have read and agreed to the published version of the manuscript.

Funding: National Natural Science Foundation of China under Grants 52302515 and 62303188, the Guangdong Basic and Applied Basic Research Foundation under Grant 2024A1515010135. Guangzhou Foundational Research Funds under Grant 2024A04J3359.

Institutional Review Board Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Goswami, D. Addressing the Challenge of Overexploitation of Natural Resources in Pursuit of Development. *Sprín J. Arts Humanit. Soc. Sci.* **2024**, *3*, 65–67. [CrossRef]

2. IEA. *Oil 2024*; IEA: Paris, France, 2024. Available online: <https://www.iea.org/reports/oil-2024> (accessed on 11 July 2025).
3. Mocera, F.; Somà, A.; Martelli, S.; Martini, V. Trends and future perspective of electrification in agricultural tractor-implement applications. *Energies* **2023**, *16*, 6601. [\[CrossRef\]](#)
4. Majeed, Y.; Khan, M.U.; Waseem, M.; Zahid, U.; Mahmood, F.; Majeed, F.; Sultan, M.; Raza, A. Renewable energy as an alternative source for energy management in agriculture. *Energy Rep.* **2023**, *10*, 344–359. [\[CrossRef\]](#)
5. Del Valle, T.M.; Yang, X.; Zhu, J.A.; Jiang, P. Evaluation of straw and agricultural policy impacts on the sustainability of the straw-based bioeconomy with an agent-based model. *Biomass Bioenergy* **2024**, *184*, 107177. [\[CrossRef\]](#)
6. Murphy, D.J.; Myers, J.; McKenzie, E., Jr.; Cavaletto, R.; May, J.; Sorensen, J. Tractors and rollover protection in the United States. *J. Agromedicine* **2010**, *15*, 249–263. [\[CrossRef\]](#) [\[PubMed\]](#)
7. Lovarelli, D.; Bacenetti, J. Exhaust gases emissions from agricultural tractors: State of the art and future perspectives for machinery operators. *Biosyst. Eng.* **2019**, *186*, 204–213. [\[CrossRef\]](#)
8. Pradhan, N.C.; Sahoo, P.K.; Kushwaha, D.K.; Makwana, Y.; Mani, I.; Kumar, M.; Aruna, T.N.; Soumya Krishnan, V. A finite element modeling-based approach to predict vibrations transmitted through different body segments of the operator within the workspace of a small tractor. *J. Field Robot.* **2023**, *40*, 1543–1561. [\[CrossRef\]](#)
9. Pradhan, N.C.; Sahoo, P.K.; Kushwaha, D.K.; Mani, I.; Kumar, M. Actuating force for transmission controls in small farm tractor considering driver's comfort. *Indian J. Agric. Sci.* **2022**, *92*, 876–881. [\[CrossRef\]](#)
10. Carabin, G.; Karaca, M.; Mazzetto, F. Preliminary results of extensive tractor rollover stability tests using a tilting-rotating rig. *Biosyst. Eng.* **2025**, *254*, 104146. [\[CrossRef\]](#)
11. Pradhan, N.C.; Sahoo, P.K.; Kushwaha, D.K.; Bhalekar, D.G.; Mani, I.; Kumar, K.; Singh, A.K.; Kumar, M.; Makwana, Y.; Soumya Krishnan, V. ANN-PID based automatic braking control system for small agricultural tractors. *J. Field Robot.* **2024**, *41*, 2805–2831. [\[CrossRef\]](#)
12. Ma, Y.; Li, Z.; Xu, Y.; Li, C.; Ding, H.; Li, C.; Tang, Q.; Liu, M.; Hou, J. The Development of No-Tillage Seeding Technology for Conservation Tillage—A Review. *Sustainability* **2025**, *17*, 1808. [\[CrossRef\]](#)
13. Lombardi, G.V.; Berni, R. Renewable energy in agriculture: Farmers willingness-to-pay for a photovoltaic electric farm tractor. *J. Clean. Prod.* **2021**, *313*, 127520. [\[CrossRef\]](#)
14. Vogt, H.H. Electric Tractor System Propelled by Solar Energy for Small-Scale Family Farming in Semiarid Regions of the Northeast of Brazil. Ph.D. Thesis, Universidade Federal do Ceará, Fortaleza, Brazil, 2018.
15. Zhu, R.; Wang, Y.; Xiang, Y.; Sun, C.; Chang, R.; Hu, G.; Gao, Z. Study on Climate Characteristics and Development Potential of Wind Energy Resources in China. *Acta Energetica Solaris Sin.* **2021**, *42*, 409–418.
16. Bungartz.nl. Siemens Tiller Tractors [EB/OL]. Available online: <http://www.bungartz.nl/Siem4mod.html> (accessed on 23 June 2022).
17. Electric Tractor, Inc. OX2 Indisputable Advantages [EB/OL]. Available online: <http://www.electrictractor.com/all-electric> (accessed on 23 June 2022).
18. Florentsev, S.; Izosimov, D.; Makarov, L.; Baida, S.; Belousov, A. Complete traction electric equipment sets of electro-mechanical drive trains for tractors. In Proceedings of the 2010 IEEE Region 8 International Conference on Computational Technologies in Electrical and Electronics Engineering (SIBIRCON), Irkutsk, Russia, 11–15 July 2010; pp. 611–616.
19. Karthik, S. John Deere GridCON Autonomous Electric Tractor. 2021. Available online: <https://electricvehicles.in/john-deere-gridcon-autonomous-electric-tractor/> (accessed on 12 December 2022).
20. Kozhushko, A. Development of Power Plants Wheel Tractors Based on Electrical Sources. 2023. Available online: <https://repository.kpi.kharkov.ua/items/560ba389-5188-4728-a793-70419e0acc7d> (accessed on 1 July 2025).
21. D'Agata, G. Research and Characterization of Battery Technologies for Railway Applications. Ph.D. Thesis, Politecnico di Torino, Torino, Italy, 2018.
22. Available online: <https://www.aiforcetech.com/productinfo/2671886.html?templateId=1745424> (accessed on 1 July 2025).
23. Gao, H.S.; Zhu, S.H. Study on design theory and method for driving line of electric tractor. *J. Nanjing Agric. Univ.* **2009**, *32*, 140–145.
24. Xu, L. Design and Selection of Power Coupling Device for Electric Tractor. *J. Mech. Transm.* **2021**. [\[CrossRef\]](#)
25. Zhang, J.; Zhao, B.; Yan, X.; Liu, M.; Xu, L.; Shang, C. Design and optimization of dual-motor electric tractor drive system based on driving cycles. *PLoS one* **2023**, *18*, e0286378. [\[CrossRef\]](#)
26. Tong, Y.; Zhang, J.; Xu, L.; Yan, X. Driving System Design and Power Source Parameter Optimization of Tractor with Dual-Motor Coupling Drive. *World Electr. Veh. J.* **2023**, *14*, 63. [\[CrossRef\]](#)
27. Lagnelöv, O.; Larsson, G.; Nilsson, D.; Larsolle, A.; Hansson, P.-A. Performance comparison of charging systems for autonomous electric field tractors using dynamic simulation. *Biosyst. Eng.* **2020**, *194*, 121–137. [\[CrossRef\]](#)
28. Xiao-lei, C.A.I.; Xiao-yong, Z.H.U.; Zhi-ling, L.; Hong-ping, J.I.A.; Lei, X.U. Design and Test of Electric Tractor Drive System Used in Greenhouse. *J. Agric. Mech. Res.* **2023**, *45*, 222–228. [\[CrossRef\]](#)

29. Troncon, D.; Alberti, L. Case of study of the electrification of a tractor: Electric motor performance requirements and design. *Energies* **2020**, *13*, 2197. [\[CrossRef\]](#)
30. Jiangyi, H.; Fan, W. Design and testing of a small orchard tractor driven by a power battery. *Eng. Agrícola* **2023**, *43*, e20220195. [\[CrossRef\]](#)
31. Bessette, D.L.; Brainard, D.C.; Srivastava, A.K.; Lee, W.; Geurkink, S. Battery Electric Tractors: Small-Scale Organic Growers' Preferences, Perceptions, and Concerns. *Energies* **2022**, *15*, 8648. [\[CrossRef\]](#)
32. Huang, S.J. A Brief Discussion on the Development and Research of Electric Tractors. *Agric. Equip. Technol.* **2021**, *47*, 43–44.
33. Wang, X.; Wang, Z.Z.; Zhou, J. Study on Control Strategy of Tandem Hybrid Tractor Considering Battery Life Decay. *J. Yunnan Agric. Univ. (Nat. Sci.)* **2023**, *38*, 529–536. [\[CrossRef\]](#)
34. Curiel-Olivares, G.; Escobar, G.; Johnson, S.; Schacht-Rodríguez, R. MPC-Based EMS for a Series Hybrid Electric Tractor. *IEEE Access* **2024**, *12*, 135999–136010. [\[CrossRef\]](#)
35. Liu, Y.N.; Deng, X.T.; Zhang, W.H.; Zhu, Y.X.; He, R.Y. Design Theory and Method Research on Tandem Hybrid Tractor Drive System. *Agric. Equip. Veh. Eng.* **2018**, *56*, 49–54.
36. Wang, Z.; Zhou, J.; Wang, X. Research on Energy Management Model for Extended-range Electric Rotary-tilling Tractor. *Trans. Chin. Soc. Agric. Mach.* **2023**, *54*, 428–438.
37. Yan, X.; Zhao, Y.; Liu, X.; Liu, M.; Wu, Y.; Zhang, J. Research on Energy Management Strategy for Series Hybrid Tractor under Typical Operating Conditions Based on Dynamic Programming. *World Electr. Veh. J.* **2024**, *15*, 156. [\[CrossRef\]](#)
38. Yang, Y.; Wen, Y.; Sun, X.; Wang, R.; Dong, Z. A Review of Green Agriculture and Energy Management Strategies for Hybrid Tractors. *Energies* **2025**, *18*, 3224. [\[CrossRef\]](#)
39. Zhao, D.; Stobart, R.; Dong, G.; Winward, E. Real-time energy management for diesel heavy duty hybrid electric vehicles. *IEEE Trans. Control. Syst. Technol.* **2014**, *23*, 829–841. [\[CrossRef\]](#)
40. Beligoi, M.; Scolaro, E.; Alberti, L.; Renzi, M.; Mattetti, M. Feasibility Evaluation of Hybrid Electric Agricultural Tractors Based on Life Cycle Cost Analysis. *IEEE Access* **2022**, *10*, 28853–28867. [\[CrossRef\]](#)
41. Kim, Y.J.; Song, B.; Kim, J. Load torque estimation for a parallel hybrid agricultural tractor in field operations. *Int. J. Precis. Eng. Manuf.* **2013**, *14*, 1865–1868. [\[CrossRef\]](#)
42. Lee, D.-H.; Kim, Y.-J.; Choi, C.-H.; Chung, S.-O.; Inoue, E.; Okayasu, T. Development of a Parallel Hybrid System for Agricultural Tractors. *J. Fac. Agric. Kyushu Univ.* **2017**, *62*, 137–144. [\[CrossRef\]](#)
43. Zhu, Z.; Zeng, L.X.; Chen, L.; Zou, R.; Cai, Y.F. Fuzzy Adaptive Energy Management Strategy for a Hybrid Agricultural Tractor Equipped with HMCVT. *Agriculture* **2022**, *12*, 1986. [\[CrossRef\]](#)
44. Deng, X.; Zhu, S.; Gao, H.; Zhang, Y. Design Theory and Method for Drive Train of Hybrid Electric Tractor. *Trans. Chin. Soc. Agric. Mach.* **2012**, *43*, 24–31+36.
45. Mocera, F.; Somà, A. Analysis of a Parallel Hybrid Electric Tractor for Agricultural Applications. *Energies* **2020**, *13*, 3055. [\[CrossRef\]](#)
46. Pascuzzi, S.; Łyp-Wrońska, K.; Gdowska, K.; Paciolla, F. Sustainability Evaluation of Hybrid Agriculture-Tractor Powertrains. *Sustainability* **2024**, *16*, 1184. [\[CrossRef\]](#)
47. Rossi, C.; Pontara, D.; Falcomer, C.; Bertoldi, M.; Mandrioli, R. A Hybrid–Electric Driveline for Agricultural Tractors Based on an e-CVT Power-Split Transmission. *Energies* **2021**, *14*, 6912. [\[CrossRef\]](#)
48. Grammatico, S.; Balluchi, A.; Cosoli, E. A series-parallel hybrid electric powertrain for industrial vehicles. In Proceedings of the 2010 IEEE Vehicle Power and Propulsion Conference, Lille, France, 1–3 September 2010; pp. 1–6.
49. Diba, F.; Esmailzadeh, E. A new parallel-series configuration for hybridization of a line-haul truck. In Proceedings of the 2013 IEEE Transportation Electrification Conference and Expo (ITEC), Detroit, MI, USA, 16–19 June 2013; pp. 1–6.
50. Wang, J.; Yang, Z.; Liu, S.; Zhang, Q.; Han, Y. A comprehensive overview of hybrid construction machinery. *Adv. Mech. Eng.* **2016**, *8*, 1687814016636809. [\[CrossRef\]](#)
51. Zhang, Y.; Li, Z.W.; Wang, C.; Xie, J. Design and simulation of driving system for electric tractor based on SRM. *J. Shanxi Agric. Univ. (Nat. Sci. Ed.)* **2018**, *38*, 69–76.
52. Xu, L.Y. Research status of the tractor transmission performance. *J. Agric. Mech.-Anization Res.* **2017**, *39*, 224–230.
53. Chen, Y.; Xie, B.; Du, Y.; Mao, E. Powertrain parameter matching and optimal design of dual-motor driven electric tractor. *Int. J. Agric. Biol. Eng.* **2019**, *12*, 33–41. [\[CrossRef\]](#)
54. Renken, F.; Wolf, J. Power electronics for hybrid-drive systems. In Proceedings of the 2007 European Conference on Power Electronics and Applications, Aalborg, Denmark, 2–5 September 2007; pp. 1–10.
55. Goswami, G.; Tupitsina, A.; Jaiswal, S.; Nutakor, C.; Lindh, T.; Sopanen, J. Comparison of various hybrid electric powertrains for non-road mobile machinery using real-time multibody simulation. *IEEE Access* **2022**, *10*, 107631–107648. [\[CrossRef\]](#)
56. Chen, Z.; Xie, B.; Luo, Z.; Liu, K.; Zhang, S.; Wen, C. Fuzzy Control Strategy for Path Tracking-Tillage Depth of Unmanned Electric Tractor Ploughing Unit. *Trans. Chin. Soc. Agric. Mach.* **2024**, *55*, 491–504.
57. Tian, Y.P.; Chen, J.; Wang, L.; Liu, M.C.; Zhao, C. Research on Real-time Monitoring System of Wheeled Tractor Slip Rate. *J. Agric. Mech. Res.* **2019**, *41*, 236–240.

58. Cao, Y.F.; Yao, M.; Sun, X.D. An Overview of Modelling and Energy Management Strategies for Hybrid Electric Vehicles. *Appl. Sci.* **2023**, *13*, 5947. [[CrossRef](#)]
59. Lee, H.-S.; Kim, J.-S.; Park, Y.-I.; Cha, S.-W. Rule-based power distribution in the power train of a parallel hybrid tractor for fuel savings. *Int. J. Precis. Eng. Manuf.-Green Technol.* **2016**, *3*, 231–237. [[CrossRef](#)]
60. Schouten, N.J.; Salman, M.A.; Kheir, N.A. Fuzzy logic control for parallel hybrid vehicles. *IEEE Trans. Control. Syst. Technol.* **2002**, *10*, 460–468. [[CrossRef](#)]
61. Wang, C.G.; Li, H. Research on Energy Management Control Strategy of the Parallel Hybrid Electric Tractor. *J. Kaifeng Univ.* **2020**, *34*, 91–96.
62. Xu, L.Y.; Zhang, J.J.; Liu, M.N.; Zhou, Z.L.; Liu, C.Q. Control algorithm and energy management strategy for extended range electric tractors. *Int. J. Agric. Biol. Eng.* **2017**, *10*, 35–44. [[CrossRef](#)]
63. Jia, C.; Qiao, W.; Qu, L. Numerical methods for optimal control of hybrid electric agricultural tractors. In Proceedings of the 2019 IEEE Transportation Electrification Conference and Expo (ITEC), Detroit, MI, USA, 19–21 June 2019; pp. 1–6.
64. Huang, T.L.; Chen, S.R.; Shi, A.P.; Li, F.Q.; Pan, C.F. Dual Motor Power Split Flow Pure Electric Tractor Energy Management Strategy. *J. Agric. Mech. Res.* **2020**, *6*, 246–250.
65. Ghobadpour, A.; Mousazadeh, H.; Kelouwani, S.; Zioui, N.; Kandidayeni, M.; Boulon, L. An intelligent energy management strategy for an off-road plug-in hybrid electric tractor based on farm operation recognition. *IET Electr. Syst. Transp.* **2021**, *11*, 333–347. [[CrossRef](#)]
66. Xu, W.X.; Xu, L.Y.; Liu, M.N.; Ma, K. Research on energy management system strategy of multi-power hybrid electric tractor. *J. Chin. Agric. Mech.* **2023**, *44*, 135–142.
67. Xu, L.Y.; Wang, Y.T.; Li, Y.Y.; Zhao, J.H.; Liu, M.N. Research on Control Strategy of APSO-Optimized Fuzzy PID for Series Hybrid Tractors. *World Electr. Veh. J.* **2023**, *14*, 258. [[CrossRef](#)]
68. Li, R.C.; Ding, X.K.; Sun, Q.Y.; Cheng, Y.; Liu, Q.; Liu, J.L.; Sun, Q. Study on Tractor Multiple Fuzzy PID Variable Universe Tillage Depth Regulation. *J. Agric. Mech. Res.* **2024**, *46*, 260–264.
69. Jia, C.; Qiao, W.; Qu, L. Modeling and control of hybrid electric vehicles: A case study for agricultural tractors. In Proceedings of the 2018 IEEE Vehicle Power and Propulsion Conference (VPPC), Chicago, IL, USA, 27–30 August 2018; pp. 1–6.
70. Dou, H.S.; Wei, H.Q.; Ai, Q.; Zhang, Y.T. Optimal energy management strategy for dual-power coupling tractor based on the adaptive control technology. *PLoS ONE* **2023**, *18*, e0292510. [[CrossRef](#)] [[PubMed](#)]
71. Dou, H.S.; Wei, H.Q.; Zhang, Y.T.; Ai, Q. Configuration Design and Optimal Energy Management for Coupled-Split Powertrain Tractor. *Machines* **2022**, *10*, 1175. [[CrossRef](#)]
72. Zhu, Z.; Zeng, L.X.; Lin, Y.G.; Chen, L.; Zou, R.; Cai, Y.F. Adaptive Energy Management Strategy for Hybrid Tractor Based on Condition Prediction. *J. Xi'an Jiaotong Univ.* **2023**, *57*, 201–210.
73. Zhang, J.J.; Feng, G.H.; Xu, L.Y.; Yan, X.H.; Wang, W.; Liu, M.N. Energy-Saving Control of Hybrid Tractors Based on Instantaneous Optimization. *World Electr. Veh. J.* **2023**, *14*, 27. [[CrossRef](#)]
74. Radrizzani, S.; Panzani, G.; Savaresi, S.M. Simultaneous energy management and speed control in a hybrid tractor with experimental validation. *IEEE Trans. Control. Syst. Technol.* **2024**, *32*, 1285–1297. [[CrossRef](#)]
75. Xie, G.; Ding, R.; Xie, H.; Qin, H.; Bian, Y. Model Predictive Control-Assisted Energy Management Strategy for Hybrid Mining Dump Trucks Based on Speed and Slope Prediction. *Electronics* **2025**, *14*, 1999. [[CrossRef](#)]
76. Curiel-Olivares, G.; Johnson, S.; Escobar, G.; Schacht-Rodríguez, R. Model Predictive Control-Based Energy Management System for a Hybrid Electric Agricultural Tractor. *IEEE Access* **2023**, *11*, 118801–118811. [[CrossRef](#)]
77. Xu, W.X.; Xu, L.Y.; Liu, M.N.; Zhang, Y.G.; Song, L.T. Research on energy management strategy of hybrid tractor based on layered decoupling. *J. Phys. Conf. Ser.* **2022**, *2343*, 012018. [[CrossRef](#)]
78. Dou, H.S.; Wei, H.Q.; Ai, Q.; Zhang, Y.T. Control Strategy for Rotary Tillage Condition of Hybrid Electric Tractor with Coupled-split Dynamic Configuration. *Trans. Chin. Soc. Agric. Mach.* **2024**, *55*, 393–400+414.
79. Wang, H.C.; Wu, H.R.; Zhu, H.J.; Miao, Y.S.; Yang, B.Z. Path optimization of unmanned agricultural machinery in vegetable field based on improved ant colony algorithm. *J. Chin. Agric. Mech.* **2023**, *44*, 187–194.
80. Zhang, J.J.; Feng, G.H.; Xu, L.Y.; Wang, W.; Yan, X.H. Energy-saving Control of Hybrid Tractor Based on Pontryagin's Minimum Principle. *Trans. Chin. Soc. Agric. Mach.* **2023**, *54*, 396–406.
81. Yang, Y.J.; Li, Z.L.; Jia, F.; Han, J.G. Control Strategy for Multi-Mode Hybrid Electric Vehicle. *Veh. Engine* **2022**, *1*, 64–70.
82. Cheng, Z.; Lu, Z.X.; Tang, D.; Jiang, C.X.; Zhou, J. PID control strategy of tractor driving anti slip control based on improved PSO algorithm. *Appl. Res. Comput.* **2017**, *34*, 83–86.
83. Li, X.; Xu, L.; Liu, M.; Yan, X.; Zhang, M. Research on torque cooperative control of distributed drive system for fuel cell electric tractor. *Comput. Electron. Agric.* **2024**, *219*, 108811. [[CrossRef](#)]
84. Zheng, B.; Song, Z.; Mao, E.; Zhou, Q.; Luo, Z.; Deng, Z.; Shao, X.; Liu, Y. An ANN-PSO-Based Method for Optimizing Agricultural Tractors in Field Operation for Emission Reduction. *Agriculture* **2022**, *12*, 1332. [[CrossRef](#)]

85. Sun, L.; Liu, M.; Wang, Z.; Wang, C.; Luo, F. Research on Load Spectrum Reconstruction Method of Exhaust System Mounting Bracket of a Hybrid Tractor Based on MOPSO-Wavelet Decomposition Technique. *Agriculture* **2023**, *13*, 1919. [\[CrossRef\]](#)
86. Pan, W.; Li, J.; Zhang, G.; Zhou, L.; Tu, M. Multi-Objective Optimization of Organic Rankine Cycle (ORC) for Tractor Waste Heat Recovery Based on Particle Swarm Optimization. *Energies* **2022**, *15*, 6720. [\[CrossRef\]](#)
87. Li, T.; Xie, B.; Wang, D.; Zhang, S.; Wu, L. Real-time adaptive energy management strategy for dual-motor-driven electric tractors. *Trans. Chin. Soc. Agric. Mach.* **2020**, *51*, 530–543.
88. Sheng, Z.P.; Xia, C.G.; Sun, Y.; Han, J.Y. Energy Management Strategy of Electric Tractor Based on Power Demand Prediction. *J. Agric. Mech. Res.* **2024**, *46*, 216–221.
89. Zhao, Y.; Xu, L.; Zhao, C.; Xu, H.; Yan, X. Research on Energy Management Strategy for Hybrid Tractors Based on DP-MPC. *Energies* **2024**, *17*, 3924. [\[CrossRef\]](#)
90. Zhang, K.; Deng, X.T.; Lu, Z.X.; Wang, T. Research on the Energy Management Strategy of a Hybrid Tractor OS-ECVT Based on a Dynamic Programming Algorithm. *Agriculture* **2024**, *14*, 1658. [\[CrossRef\]](#)
91. Plerou, A.; Vlamou, E.; Papadopoulos, V. Fuzzy genetic algorithms: Fuzzy logic controllers and genetics algorithms. *Glob. J. Res. Anal.* **2016**, *5*, 497–500.
92. Li, Y.Y.; Liu, M.N.; Xu, L.Y.; Lei, S.H. Control strategy of series hybrid tractor based on nonlinear program genetic algorithm. *J. Jiangsu Univ. (Nat. Sci. Ed.)* **2023**, *44*, 166–172+185.
93. Xie, Z.H.; Wang, P.; Gu, B.X.; Ji, C.Y.; Tian, G.Z. Application of genetic algorithm based on group and elite strategy for robot navigation. *J. South China Agric. Univ.* **2017**, *38*, 110–116.
94. Lü, X.; Wu, Y.; Lian, J.; Zhang, Y.; Chen, C.; Wang, P.; Meng, L. Energy management of hybrid electric vehicles: A review of energy optimization of fuel cell hybrid power system based on genetic algorithm. *Energy Convers. Manag.* **2020**, *205*, 112474. [\[CrossRef\]](#)
95. Zhou, B.; Su, X.; Yu, H.; Guo, W.; Zhang, Q. Research on Path Tracking of Articulated Steering Tractor Based on Modified Model Predictive Control. *Agriculture* **2023**, *13*, 871. [\[CrossRef\]](#)
96. Wang, L.; Zhai, Z.; Zhu, Z.; Mao, E. Path Tracking Control of an Autonomous Tractor Using Improved Stanley Controller Optimized with Multiple-Population Genetic Algorithm. *Actuators* **2022**, *11*, 22. [\[CrossRef\]](#)
97. Chen, H.; Xie, H.; Sun, L.; Shang, T. Research on Tractor Optimal Obstacle Avoidance Path Planning for Improving Navigation Accuracy and Avoiding Land Waste. *Agriculture* **2023**, *13*, 934. [\[CrossRef\]](#)
98. Yang, M.; Sun, X.; Deng, X.; Lu, Z.; Wang, T. Extrapolation of Tractor Traction Resistance Load Spectrum and Compilation of Loading Spectrum Based on Optimal Threshold Selection Using a Genetic Algorithm. *Agriculture* **2023**, *13*, 1133. [\[CrossRef\]](#)
99. Fan, X.; Wang, J.; Wang, H.; Yang, L.; Xia, C. LQR Trajectory Tracking Control of Unmanned Wheeled Tractor Based on Improved Quantum Genetic Algorithm. *Machines* **2023**, *11*, 62. [\[CrossRef\]](#)
100. Li, B.; Pan, J.; Li, Y.; Ni, K.; Huang, W.; Jiang, H.; Liu, F. Optimization Method of Speed Ratio for Power-Shift Transmission of Agricultural Tractor. *Machines* **2023**, *11*, 438. [\[CrossRef\]](#)
101. Yang, Y.Q.; Zhang, J.L.; Wang, D.Y.; Zheng, D.C. Gear train optimization of 404p tractor based on multi-objective genetic algorithm. *Agric. Eng.* **2022**, *12*, 91–96.
102. Wu, Y.; Zhao, Y.; Wen, C.; Zhang, J.; Yan, X. Research on energy management strategies for high-power diesel-electric hybrid tractors based on double deep Q-network. *Sci. Rep.* **2025**, *15*, 17130. [\[CrossRef\]](#)
103. Dou, H.S.; Zhang, Y.T.; Ai, Q.; Zhao, X.Q. Control strategy for hybrid tractor plow conditions oriented to coupled-split dynamic configuration. *Trans. Chin. Soc. Agric. Eng.* **2022**, *38*, 41–49.
104. Chen, B.; Ma, R.; Zhou, Y.; Ma, R.; Jiang, W.; Yang, F. Co-optimization of speed planning and cost-optimal energy management for fuel cell trucks under vehicle-following scenarios. *Energy Convers. Manag.* **2024**, *300*, 117914. [\[CrossRef\]](#)
105. Watkins, C.J.C.H. Learning from Delayed Rewards. Ph.D. Thesis, King's College London, London, UK, 1989.
106. Liu, T.; Wang, B.; Yang, C. Online Markov Chain-based energy management for a hybrid tracked vehicle with speedy Q-learning. *Energy* **2018**, *160*, 544–555. [\[CrossRef\]](#)
107. Wu, J.; He, H.; Peng, J.; Li, Y.; Li, Z. Continuous reinforcement learning of energy management with deep Q network for a power split hybrid electric bus. *Appl. Energy* **2018**, *222*, 799–811. [\[CrossRef\]](#)
108. Han, X.; He, H.; Wu, J.; Peng, J.; Li, Y. Energy management based on reinforcement learning with double deep Q-learning for a hybrid electric tracked vehicle. *Appl. Energy* **2019**, *254*, 113708. [\[CrossRef\]](#)
109. Xu, B.; Rathod, D.; Zhang, D.; Yebi, A.; Zhang, X.; Li, X.; Filipi, Z. Parametric study on reinforcement learning optimized energy management strategy for a hybrid electric vehicle. *Appl. Energy* **2020**, *259*, 114200. [\[CrossRef\]](#)
110. Wang, Y.; Liu, X.; Ren, Z.; Yao, Z.; Tan, X. Synchronized path planning and tracking for front and rear axles in articulated wheel loaders. *Autom. Constr.* **2024**, *165*, 105538. [\[CrossRef\]](#)
111. Olcay, E.; Rui, X.; Wang, R. Headland Turn Automation Concept for Tractor-Trailer System with Deep Reinforcement Learning. In Proceedings of the 2023 IEEE 19th International Conference on Automation Science and Engineering (CASE), Auckland, New Zealand, 30 August 2023; pp. 1–7.

112. Elhaki, O.; Shojaei, K. Output-feedback robust saturated actor–critic multi-layer neural network controller for multi-body electrically driven tractors with n-trailer guaranteeing prescribed output constraints. *Robot. Auton. Syst.* **2022**, *154*, 104106. [\[CrossRef\]](#)
113. Xiao, B.; Yang, W.; Wu, J.; Walker, P.D.; Zhang, N. Energy management strategy via maximum entropy reinforcement learning for an extended range logistics vehicle. *Energy* **2022**, *253*, 124105. [\[CrossRef\]](#)
114. Drungilas, D.; Kurmis, M.; Senulis, A.; Lukosius, Z.; Andziulis, A.; Januteniene, J.; Bogdevicius, M.; Jankunas, V.; Voznak, M. Deep reinforcement learning based optimization of automated guided vehicle time and energy consumption in a container terminal. *Alex. Eng. J.* **2023**, *67*, 397–407. [\[CrossRef\]](#)
115. Qi, C.; Zhu, Y.; Song, C.; Yan, G.; Xiao, F.; Zhang, X.; Cao, J.; Song, S. Hierarchical reinforcement learning based energy management strategy for hybrid electric vehicle. *Energy* **2022**, *238*, 121703. [\[CrossRef\]](#)
116. Lian, R.; Peng, J.; Wu, Y.; Tan, H.; Zhang, H. Rule-interposing deep reinforcement learning based energy management strategy for power-split hybrid electric vehicle. *Energy* **2020**, *197*, 117297. [\[CrossRef\]](#)
117. Zhang, Y.G.; Liu, M.N.; Xu, W.X.; Xu, L.Y. Parameter optimization of electric tractor dual motor coupling drive based on DDPG algorithm. *J. Chin. Agric. Mech.* **2023**, *44*, 129–136.
118. Tang, X.; Chen, J.; Pu, H.; Liu, T.; Khajepour, A. Double deep reinforcement learning-based energy management for a parallel hybrid electric vehicle with engine start–stop strategy. *IEEE Trans. Transp. Electr.* **2021**, *8*, 1376–1388. [\[CrossRef\]](#)
119. Tang, X.; Chen, J.; Liu, T.; Qin, Y.; Cao, D. Distributed deep reinforcement learning-based energy and emission management strategy for hybrid electric vehicles. *IEEE Trans. Veh. Technol.* **2021**, *70*, 9922–9934. [\[CrossRef\]](#)
120. Lin, J.Q.; Wang, H.J.; Zou, X.J.; Zhang, P.; Li, C.E. Obstacle Avoidance Path Planning and Simulation of Mobile Picking Robot Based on DPPO. *J. Syst. Simul.* **2023**, *35*, 1692–1704.
121. Yang, N.; Ruan, S.; Han, L.; Liu, H.; Guo, L.; Xiang, C. Reinforcement learning-based real-time intelligent energy management for hybrid electric vehicles in a model predictive control framework. *Energy* **2023**, *270*, 126791. [\[CrossRef\]](#)
122. Zhou, Q.; Li, J.; Shuai, B.; Williams, H.; He, Y.; Li, Z.; Xu, H.; Yan, F. Multi-step reinforcement learning for model-free predictive energy management of an electrified off-highway vehicle. *Appl. Energy* **2019**, *255*, 113755. [\[CrossRef\]](#)
123. Zhang, W.; Gai, J.; Zhang, Z.; Tang, L.; Liao, Q.; Ding, Y. Double-DQN based path smoothing and tracking control method for robotic vehicle navigation. *Comput. Electron. Agric.* **2019**, *166*, 104985. [\[CrossRef\]](#)
124. Zhang, X.; Wang, X.; Yuan, P.; Tian, H.; Shu, G. Optimizing hybrid electric vehicle coupling organic Rankine cycle energy management strategy via deep reinforcement learning. *Energy AI* **2024**, *17*, 100392. [\[CrossRef\]](#)
125. Zhang, Y.; Zhao, W.; Wang, J.; Yuan, Y. Recent progress, challenges and future prospects of applied deep reinforcement learning: A practical perspective in path planning. *Neurocomputing* **2024**, *608*, 128423. [\[CrossRef\]](#)
126. Hafner, D.; Pasukonis, J.; Ba, J.; Lillicrap, T. Mastering diverse control tasks through world models. *Nature* **2025**, *640*, 647–653. [\[CrossRef\]](#)
127. Song, H.; Jiang, J.; Min, Y.; Chen, J.; Chen, Z.; Zhao, W.X.; Fang, L.; Wen, J.-R. R1-searcher: Incentivizing the search capability in llms via reinforcement learning. *arXiv* **2025**, arXiv:2503.05592. [\[CrossRef\]](#)
128. Shao, Z.; Wang, P.; Zhu, Q.; Xu, R.; Song, J.; Bi, X.; Zhang, H.; Zhang, M.; Li, Y.; Wu, Y. Deepseekmath: Pushing the limits of mathematical reasoning in open language models. *arXiv* **2024**, arXiv:2402.03300.
129. Hoang, T.; Le, H.; Becker, P.; Ngo, V.A.; Neumann, G. Geometry-aware RL for Manipulation of Varying Shapes and Deformable Objects. *arXiv* **2025**, arXiv:2502.07005.
130. Li, X.; Wang, X.; Bai, C.; Zhang, J. Exponential Topology-enabled Scalable Communication in Multi-agent Reinforcement Learning. *arXiv* **2025**, arXiv:2502.19717.
131. Wang, T.; Xu, X.; Wang, C.; Li, Z.; Li, D. From Smart Farming towards Unmanned Farms: A New Mode of Agricultural Production. *Agriculture* **2021**, *11*, 145. [\[CrossRef\]](#)
132. Wang, N.; Li, S.; Xiao, J.; Wang, T.; Han, Y.; Wang, H.; Zhang, M.; Li, H. A collaborative scheduling and planning method for multiple machines in harvesting and transportation operations-Part I: Harvester task allocation and sequence optimization. *Comput. Electron. Agric.* **2025**, *232*, 110060. [\[CrossRef\]](#)
133. Wang, N.; Yang, X.; Wang, T.; Xiao, J.; Zhang, M.; Wang, H.; Li, H. Collaborative path planning and task allocation for multiple agricultural machines. *Comput. Electron. Agric.* **2023**, *213*, 108218. [\[CrossRef\]](#)
134. Man, Z.X.; He, J.; Liu, S.Q.; Yue, M.D.; Hu, L. Method and test for operating multi-machine cooperative harvesting in intelligent agricultural machinery. *Trans. Chin. Soc. Agric. Eng.* **2024**, *40*, 17–26.
135. Zhang, W.Y.; Zhang, Z.G.; Zhang, F.; Ding, F.; Hu, L. Cooperative autonomous operation strategy and experiment of the rice harvester together with a rice-transporting vehicle. *Trans. Chin. Soc. Agric. Eng.* **2022**, *38*, 1–9.
136. Zhang, W.; Hu, L.; Ding, F.; Luo, X.; Zhang, Z.; Hu, L.; Huang, P.; Peng, M. Parking precise alignment control and cotransporter system for rice harvester and transporter. *Comput. Electron. Agric.* **2023**, *215*, 108443. [\[CrossRef\]](#)
137. Hu, L.; Guan, J.J.; He, J.; Man, Z.X.; Tian, L. Design and Experiment of Automatic Driving Operation System of Peanut Harvester Based on BDS. *Trans. Chin. Soc. Agric. Mach.* **2022**, *53*, 21–27.

138. He, J.; Man, Z.X.; Hu, L.; Luo, X.W.; Wang, P. Path tracking control method and experiments for the crawler-mounted peanut combine harvester. *Trans. Chin. Soc. Agric. Eng.* **2023**, *39*, 9–17.
139. Ding, F.; Zhang, W.Y.; Luo, X.W.; Hu, L.; Zhang, Z.G.; Wang, M.C.; Li, H.K.; Peng, M.D.; Wu, X.L.; Hu, L.W.; et al. Gain self-adjusting single neuron PID control method and experiments for longitudinal relative position of harvester and transport vehicle. *Comput. Electron. Agric.* **2023**, *213*, 108215. [[CrossRef](#)]
140. Zhang, W.Y.; Hu, L.W.; Wang, H.; Zhang, G.C.; Luo, X.W. Improved Pure Pursuit Agricultural Machinery Navigation Curve Path Tracking Method Based on B-spline Optimization. *Trans. Chin. Soc. Agric. Mach.* **2024**, *55*, 42–51+115.
141. He, J.; Liu, S.Q.; Man, Z.X.; Yue, M.D.; Wang, J.T. Curve Path Tracking Control of Agricultural Machinery Automatic Driving Based on Full State Feedback Control. *Trans. Chin. Soc. Agric. Mach.* **2025**, *56*, 145–154.
142. He, J.; Zeng, H.X.; Li, M.J.; He, J.; Mo, J.J.; Wang, P.; Zhao, R.M. Improved Pure Pursuit Path Tracking Control Method for Automatic Navigation Tractor Based on Drive Wheel Lateral Deviation Compensation. *Trans. Chin. Soc. Agric. Mach.* **2025**, *56*, 28–37.
143. He, J.; Luo, X.; Zhang, Z.; Wang, P.; He, J.; Yue, B.; Ding, F.; Zhu, Q. Positioning correction method for rice transplanters based on the attitude of the implement. *Comput. Electron. Agric.* **2020**, *176*, 105598. [[CrossRef](#)]
144. He, J.; Hu, L.; Wang, P.; Liu, Y.; Man, Z.; Tu, T.; Yang, L.; Li, Y.; Yi, Y.; Li, W.; et al. Path tracking control method and performance test based on agricultural machinery pose correction. *Comput. Electron. Agric.* **2022**, *200*, 107185. [[CrossRef](#)]
145. Hu, L.; Zhang, H.; He, J.; Man, Z.X.; Yue, M.D.; Qu, G.K.; Tang, Q.Y.; Huang, P.K.; Luo, X.W. Path Planning Technical Research of Low-rolling Compaction Harvesting Operation for the First Season of Ratoon Rice. *Trans. Chin. Soc. Agric. Mach.* **2025**, *56*, 19–27.
146. Zhang, Z.G.; Wang, G.M.; Luo, X.W.; He, J.; Wang, J. Detection Method of Steering Wheel Angle for Tractor Automatic Driving. *Trans. Chin. Soc. Agric. Mach.* **2019**, *50*, 352–357.
147. He, J.; Zhu, J.G.; Luo, X.W.; Zhang, Z.G.; Hu, L. Design of steering control system for rice transplanter equipped with steering wheel-like motor. *Trans. Chin. Soc. Agric. Eng.* **2019**, *35*, 10–17.
148. Available online: <https://www.deere.com/en/technology-products/precision-ag-technology/data-management/jdlink/> (accessed on 13 July 2025).
149. Jiang, D.; Shen, Z.; Zheng, Q.; Zhang, T.; Xiang, W.; Jin, J. Farm-LightSeek: An Edge-centric Multimodal Agricultural IoT Data Analytics Framework with Lightweight LLMs. *IEEE Internet of Things Magazine*, 6 June 2025; pp. 1–6.
150. Fendt e100 V Vario. Available online: <https://www.fendt.com/int/agricultural-machinery/e-tractors/fendt-e100-v-vario> (accessed on 10 July 2025).
151. Luo, X.W.; Liao, J.; Hu, L.; Zhou, Z.Y.; Zhang, Z.G.; Zang, Y.; Wang, P.; He, J. Research progress of intelligent agricultural machinery and practice of unmanned farm in China. *J. South China Agric. Univ.* **2021**, *42*, 8–17. [[CrossRef](#)]
152. News. Sciencenet. Available online: <https://news.sciencenet.cn/sbhtmlnews/2020/5/355053.shtml?id=355053> (accessed on 19 July 2025).
153. GB/T 16877-2008; Prohibition and Scrapping for Tractors. Standardization Administration of China: Beijing, China, 2008. (In Chinese)
154. GB/T15370.1-2012; General Requirement of Agricultural Tractors—Part 1: Under 50 kW Wheeled Tractors. Standardization Administration of China: Beijing, China, 2012. (In Chinese)
155. GB/T 15370.2-2009; General Requirement of Agricultural Tractors—Part 2: 50 kW~130 kW Wheeled Tractors. Standardization Administration of China: Beijing, China, 2009. (In Chinese)
156. Usage Price: Electricity for industry: 35 kV & Above:Guangzhou. Available online: [https://www.ceicdata.com/en/china/electricity-price-36-city/cn-usage-price-electricity-for-industry-35-kv-\[-\]-above-guangzhou](https://www.ceicdata.com/en/china/electricity-price-36-city/cn-usage-price-electricity-for-industry-35-kv-[-]-above-guangzhou) (accessed on 19 July 2025).
157. Gao, H.; Xue, J. Modeling and economic assessment of electric transformation of agricultural tractors fueled with diesel. *Sustain. Energy Technol. Assess.* **2020**, *39*, 100697. [[CrossRef](#)]
158. Proctor, K. Total Cost of Ownership of a Compact Battery Electric Agricultural Tractor. 2022. Available online: https://static1.squarespace.com/static/656a0f83560384720ffc2a8c/t/6626c0cfff2241134020a818/1713815760384/TCO_report_May%2B2022.pdf (accessed on 19 July 2025).

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.