

A review on the powertrains and energy management strategies of electric tractors

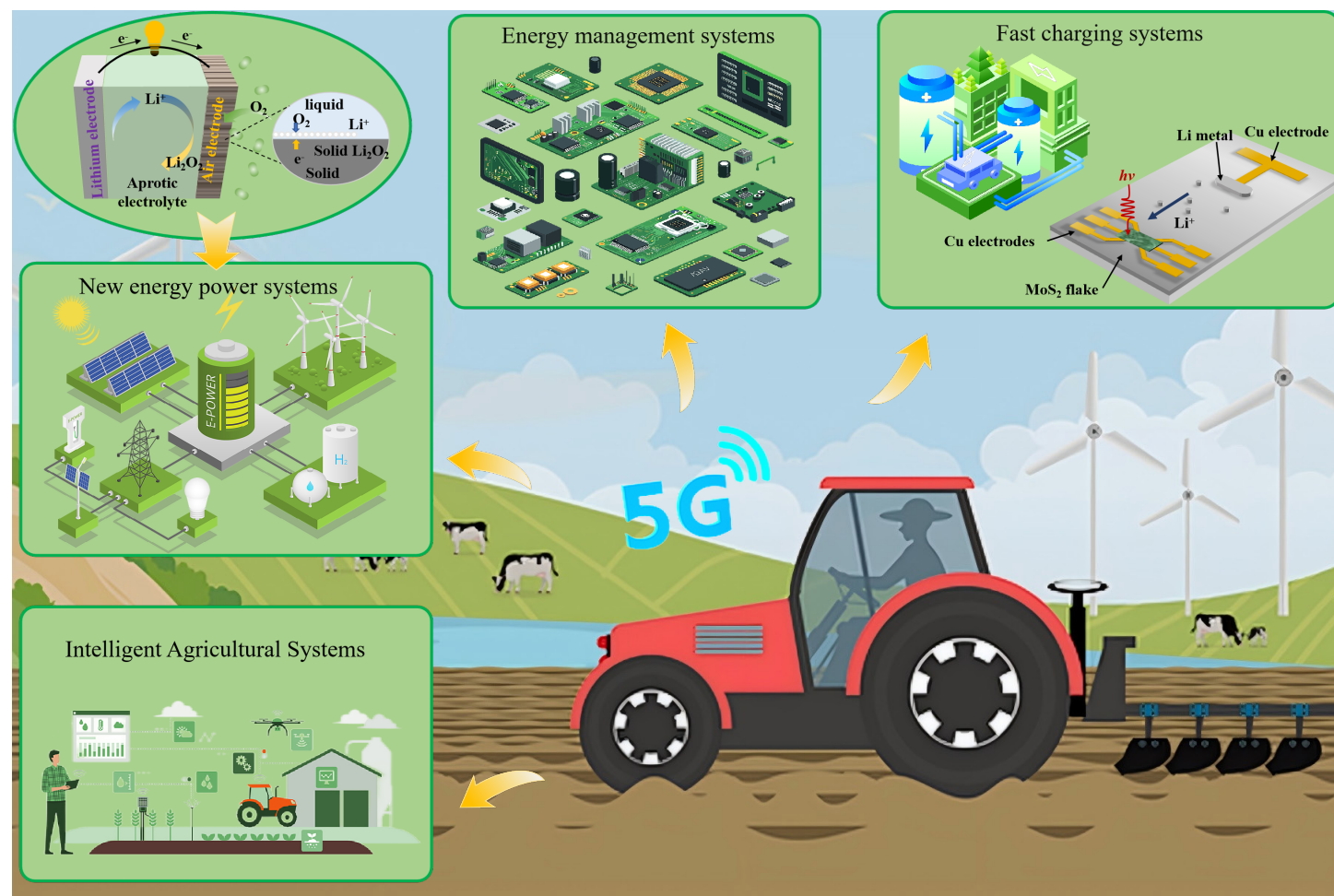
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GRAPHICAL ABSTRACT



PUBLIC SUMMARY

- Reviews and classifications of powertrains for electric tractors are conducted.
- Energy management strategies with powertrains in electric tractors are reviewed.
- Trend and research hotspots of energy management with electric tractors are analyzed.
- A guide for research on energy management strategies and powertrains of electric tractors is provided.

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Given the increasing demand for sustainable agricultural practices and energy conservation, advanced technologies for electric agricultural machinery (EAM) are critically needed. This paper provides a comprehensive review and analysis of powertrain systems and energy management strategies (EMSs) for electric tractors (ETs), a key representative of EAM. Specifically, this paper: (1) outlines the current development status and research significance of ET powertrains, including single-energy powertrains (SEPs), diesel-electric hybrid powertrains (DEHPs), and hybrid energy storage systems (HESSs); (2) offers an in-depth analysis of EMS approaches—covering rule-based, optimization-based, and learning-based strategies—and evaluates their performance in terms of energy efficiency, adaptability, and cost reduction; (3) identifies future research hotspots, such as intelligent data-driven EMSs, multi-source energy integration, and advanced energy optimization algorithms to improve the adaptability, efficiency, and reliability of ET power systems. The findings of this paper highlight the critical role of hybrid powertrains and advanced EMSs in enhancing the operational range, energy efficiency, and economic viability of ETs, offering insights and guidance for the further development of sustainable agricultural technologies.

INTRODUCTION

The "Green Revolution" and agricultural transformation^{1–3} arrived in the mid-20th century. Global food production from agriculture increased dramatically as a result of the increased use of manufactured machinery.^{4–5} However, there was also significant environmental damage during this time of increased agricultural intensity.^{6–8} The Food and Agriculture Organization (FAO) has recommended three essential components of agricultural production: increasing income and productivity; addressing climate change with flexibility; and lowering or completely eliminating greenhouse gas emissions.⁹ But there has always been a certain conflict between environmental preservation and higher productivity. This is because using more types of AM to support human labor is necessary to increase productivity. But due to growing investments in AM, poor fuel-powered agricultural equipment maintenance, and a lack of appropriate pollution control laws, substantial emissions from AM are deteriorating the quality of the air and the environment and endangering the viability of agriculture.^{10–12} According to studies, there are significant carbon emissions from diesel-powered AMs when they are operating in the field. The production of sunflowers, for instance, has been shown to emit 67.176 kg of CO₂ equivalent per hectare (3 point29 percent),¹³ whereas the carbon emissions from machinery used to cultivate rice, wheat, and maize, respectively, account for 13%, 25%, and 20% of the total emissions.¹⁴ According to reports, Australia's total carbon emissions are 7% caused by emissions from cotton production, with AM contributing 16% of these emissions.

Tractors, loaders, trucks, combine harvesters, and irrigation-related equipment are the primary components of agricultural machinery (AM).¹⁵ Among these, tractors play a versatile role in agricultural production, as they can be

equipped with various implements to perform tasks such as planting, plowing, harvesting, and mowing.¹⁶ As the largest agricultural producer globally, China has pursued a development strategy focused on agricultural mechanization since the 1950s. As shown in Figure 1, the increase in power equipment, including tractors, and machinery such as water pumps and harvesters, has substantially improved the mechanization rate in crop production, from 34% in 2004 to 72% in 2022. However, tractors are still predominantly diesel-powered. The entire AM power in China as of 2019 was 102.76 million kilowatts (KW), of which 77.6% came from diesel engine power, according to the 2022 China AM Industry Yearbook.¹⁷ Tractors with diesel engines are now the main source of pollution endangering agricultural environments.¹⁸ According to data from the 2019 China Mobile Source Environmental Management Annual Report, tractor emissions of nitrogen oxides (NO_x) accounted for 59.0% of total AM for NO_x emissions, while particulate matter (PM) emissions accounted for 60.1%.¹⁹ In China, the amount of pollution released by large and medium-sized tractors by 2021 was 663,000 tons, while the amount released by small tractors was 441,000 tons. Nitrogen oxide (NO_x) emissions from tractors alone accounted for 58% of all emissions from non-road mobile sources. By contrast, particulate matter (PM) and hydrocarbon (HC) emissions made up 21% and 50% of all emissions, respectively.²⁰ Many laws and regulations have been passed by nations all over the world in response to the pollution that AM, particularly from tractors, causes. The United States Environmental Protection Agency (EPA) and the European Union (EU), for instance, have established regulations governing exhaust emissions from automobiles, trucks, ships, and AM (particularly tractors) during fuel combustion. Tractor engines are subject to stringent European regulations (97/68/EC, 2010/22/EU, 2010/26/EU) that strictly limit the emissions of NO_x, CO, PM, and HC.²¹ To address AM emissions, the agricultural sectors are actively investigating sustainable energy technologies in addition to policy regulations. Presently, AM, particularly tractors, have solutions thanks to new energy powertrains used in automobiles and engineering vehicles, such as hybrid and pure electric powertrains. Hybrid powertrains, which combine the benefits of two distinct energy sources, are the recommended substitute for conventional fuel powertrains among them. These days, hybrid powertrains can be found with an engine and battery, a fuel cell and battery, or a solar cell and battery. The utilization of hybrid powertrains offers notable benefits in terms of increased fuel efficiency, decreased emissions, safety, noise reduction, and reduced overall weight of the vehicle.²²

Three primary technologies are thought to be essential to the field of new energy vehicles: vehicle control, energy management, and battery management.^{23,24} To effectively reduce emissions and achieve efficient power performance, energy management strategies (EMSs), are essential. The most efficient way to divide up the power demands among all power sources is called energy management in hybrid powertrain systems.²⁵ ETs seek single- or multi-objective optimization by coordinating the powertrain system's energy distribution based on vehicle power demands, system operating conditions, and the distinctive qualities of various power sources.^{26,27} EMSs aim to accomplish this. But given the complicated nonlinear structure of powertrain

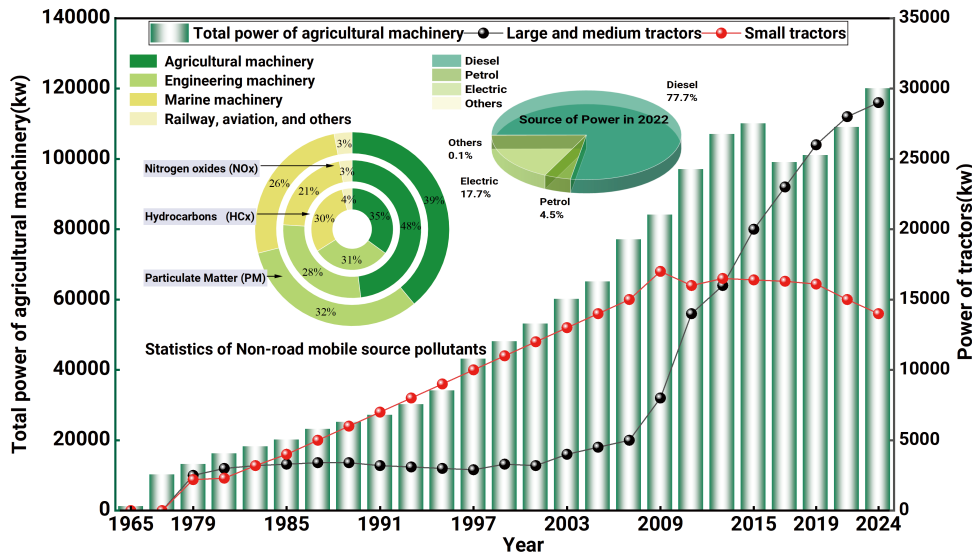


Figure 1. Mechanization rate in crop production in China from 1965 to 2024.

ScienceDirect. A range of keyword combinations, including "hybrid tractor," "electric tractor," "energy management," and "power management," is used to identify pertinent studies. Only articles published between 2013 and 2023 are considered. **CiteSpace** is employed to visualize knowledge structures, trends, and distributions in this research field.³⁴ The results of bibliometric analysis of power systems and EMSs for ETs is shown in Figure 3.

As shown in Figure 3A, a total of 62 papers were published between January 2013 and December 2023 when searching with the keywords "electric tractor" and "hybrid tractor." Additionally, it also reveals that annual publications peaked at 125 in 2023, with 2019 showing

the fastest growth rate at 47.5%. Additionally, Figure 3B shows that China (118 publications, 18.67%), the United States (80 publications, 12.66%), and Russia (80 publications, 12.66%) are the leading nations/regions in electric tractor research during this period. The top 20 national research institutions in the world for ET research from January 2013 to December 2023 are displayed in Figure 3B. Schlumberger (British Virgin Islands) comes in third with 8 publications, behind China Agricultural University and Henan University of Science and Technology, which come in first and second place, respectively, with 20 and 19 publications. This demonstrates the prominent role those Chinese institutions have taken in electric tractor research, to which Russia and the United States have also made substantial contributions. A keyword co-occurrence map is shown in Figure 3C, where the color of the connections indicates the publication time and the size of the nodes indicates the frequency of keyword occurrences. The terms "energy management," "system," "hybrid," "battery," "fuel cell," "air pollution," "performance," and "model" are among the most frequently occurring high-frequency keywords. Key research areas in ET power systems and EMSs are highlighted by these keywords.

After further refining the keywords to "energy management" and "power systems," 126 relevant papers were found. The 126 studies that are directly related to drivelines and EMS are shown in Figure 4's annual publication trends. More specifically, roughly three papers were published annually in 2013 and 2014. Approximately six papers were published yearly in 2015 and 2016. In 2017, there were roughly 13 papers; in 2018, there were about 7 papers; and in 2019, there were roughly 17 papers. Twenty papers or so were published in 2020; these were followed by nine papers in 2022, nine papers in 2021, and roughly seven papers in 2023. These figures show a general pattern of consistent publication growth, with a notable uptick after 2017, demonstrating the expanding significance of ET research.

Additionally, research trends in powertrain configurations are also depicted in Figure 4A, which includes diesel-electric hybrid power (DEHP) systems, hybrid energy storage systems (HESS), and single-source powertrains.⁷ The data indicates that because of their adaptability and effectiveness in tackling a range of energy management issues in ETs, DEHPs account for 64.77% of the research focus. Single-source powertrains received 8.82% of the focus because of their limitations, whereas HESSs received 26.47%, indicating a strong interest in alternative energy storage solutions. Numerous investigations have classified EMSs. Additionally, EMSs for ET were analyzed based on these classifications, as shown in Figure 4B. It can be seen that rule-based EMS is predominant, with deterministic approaches contributing at 42.42%, real-time optimization at 21.21%, and fuzzy logic control (FLC) at 18.18% among the methods. Combined approaches make up 6.06% of EMS, while global optimization-based EMS accounts for 12.12%. Additionally, it also can be seen that the validation techniques: 36.36% use Hardware-in-the-Loop (HiL)¹⁷⁶ testing, and 63.64% use software simulations.

Keyword and bibliometric analyses indicate that the research focus for ETs

systems, the unpredictability of driving conditions, and the need for real-time performance in online applications, creating effective and adaptive EMSs for ETs has become considerably more difficult.²⁸

Power distribution needs to be managed by ETs using efficient control strategies in order to meet power demands under different load conditions, including light (transportation, seeding), medium (fertilization, weeding), and heavy loads (plowing).²⁹ Optimizing powertrain performance and energy efficiency requires an appropriate EMS to adjust to these circumstances.^{30–33} Research on electric vehicle sensors, or EMSs, has been a hot topic recently, according to the authors' review of the literature. In terms of their design, power characteristics, and operational settings, ETs are not like electric vehicles at all. Reviews and analysis of ET power systems and energy management that are thorough are currently lacking. Thus, an extensive review of ET power systems and their energy management techniques is given in order to further the development of ETs and support rural new energy technologies. In addition to offering references and recommendations for additional research, this paper aims to assist researchers in related fields in better understanding the current status and trends of powertrain systems and energy management issues with ETs by investigating and summarizing the EMSs and powertrain systems of ETs.

The following summarizes the main contributions:

Comprehensive Review: By providing an extensive analysis of current research trends and developments, this review fills a gap in the literature by providing a thorough analysis of ET power systems and EMSs.

Bibliometric Analysis: A thorough bibliometric analysis, highlighting important research areas and indicating future directions in the field of ET powertrain systems and EMSs, is provided in this study using **CiteSpace**.

Classification and Assessment: The benefits and drawbacks of ET powertrains are assessed after they have been classified. Different EMS strategies are explained, including the newest control systems and their drawbacks.

Future Research Directions: This work offers insightful analysis and recommendations for future research, fostering breakthroughs in rural new energy technologies, by highlighting the difficulties and possibilities in ET powertrain and EMS development.

The remainder of the work is structured as follows: Section 2 reviews the development history and current research hotspots before presenting the bibliometric analysis of power systems and EMSs for ETs. ET powertrain control strategies are reviewed and analyzed in Section 3. An outline of EMS control strategies is given in Section 4. Challenges and future trends are covered in Section 5. Section 6 provides an explanation of the outcome. The general framework of the thesis is shown in Figure 2.

BIBLIOMETRIC ANALYSIS OF POWER SYSTEMS AND EMSs FOR ETs

The primary aim of this research is to review power propulsion systems and power allocation techniques for electric tractors (ETs). Relevant literature is systematically gathered from databases such as Scopus, IEEE, and

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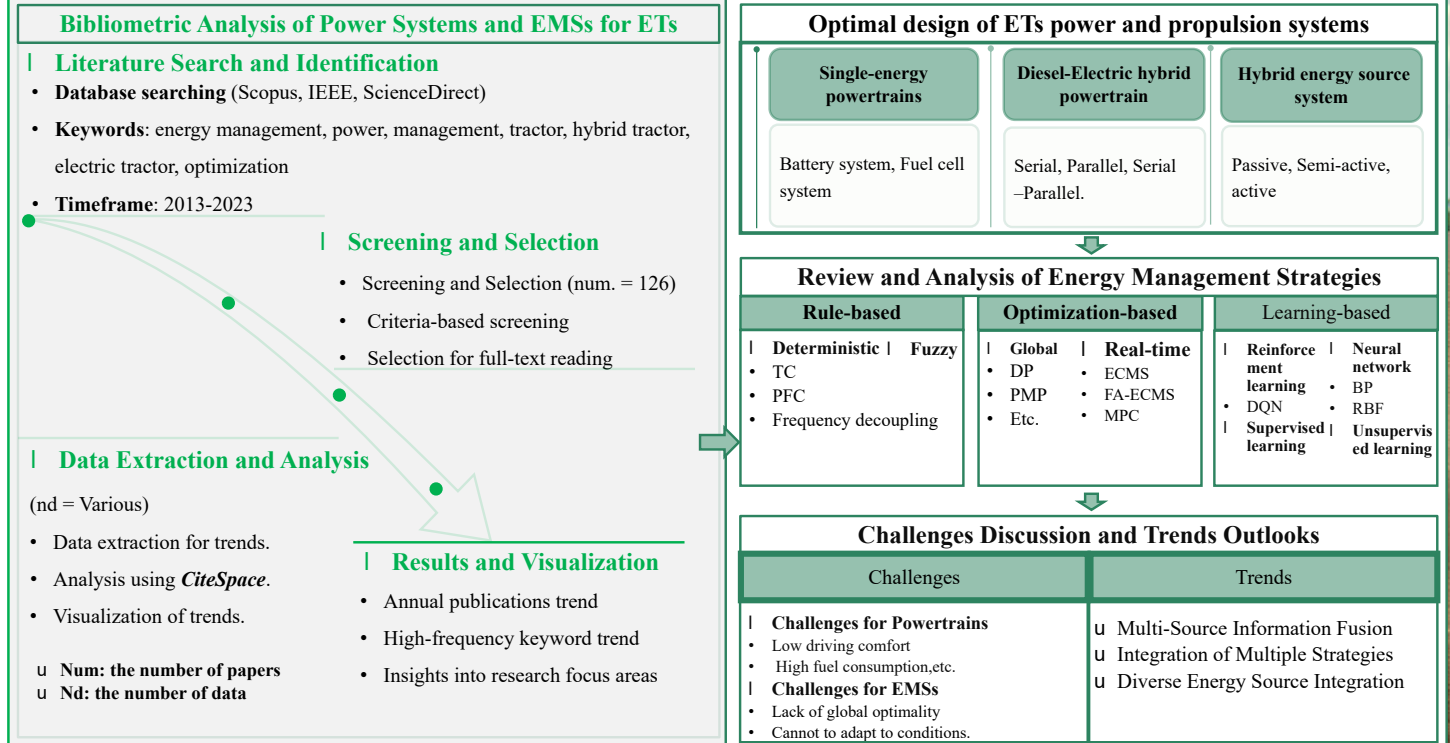


Figure 2. Mechanization rate in crop production in China from 1965 to 2024.

is primarily on optimizing power propulsion systems and efficient EMS. Additionally, the performance validation of energy management methods is crucial. These three aspects will be analyzed in detail in the following sections.

OPTIMAL DESIGN OF ETS POWERTRAINS

Ref. [35-36] contains a detailed development history of ETs, summarizing the advancements made by leading tractor manufacturers like John Deere, AVL, Fendt, Soletrac, Ztractor, Rigitrac, Claas, Case IH, Escorts, Kubota, and Schaffer in the electrification and automation of agricultural tractors. An outline of the hybrid agricultural tractor development timeline from 1954 to 2022 is presented in Figure 5.³⁵ For this study, the structure is summarized by the powertrain. The power systems of different types of ETs can be categorized into single-energy powertrains (SEPs), diesel-electric hybrid powertrains (DEHPs), and hybrid energy storage systems (HESSs) based on the energy source. A comprehensive analysis of powertrain topology and its parameters is essential, as different architectures have a substantial influence on powertrain performance. The subsequent section provides an in-depth explanation of various powertrain architectures. Finally, methodologies for system selection and comparative evaluation are discussed.

Single-energy powertrain (SEP)

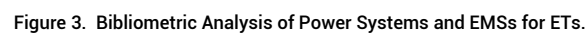
Single-energy powertrains (SEPs), only use one kind of energy source. For example, rechargeable batteries power electric motors, a powertrain that is zero-emission, quiet and efficient. For instance, Ref. [37-38] introduced the John Deere SESAM (Figure 6A) with a 130-kWh battery that operates for 4 hours but takes up to 3 hours to recharge and has a battery life of only 3,100 charge cycles. Ref. [39] introduces the New Holland NH₂ hydrogen-powered tractor Figure 6B, which can accelerate by directly increasing the fuel cell output power. It refuels faster, saving 50% of the time compared to charging electric powertrains. However, the prototype's total cost is comparable to that of a conventional tractor, with fuel cell costs accounting for 30% of the total. Other examples include the Fendt e100 Vario (Figure 6D), which supports fast charging but is hindered by high initial costs and limited infrastructure, and the Soletrac eUtility (Figure 6C), suitable for small farms but restricted to

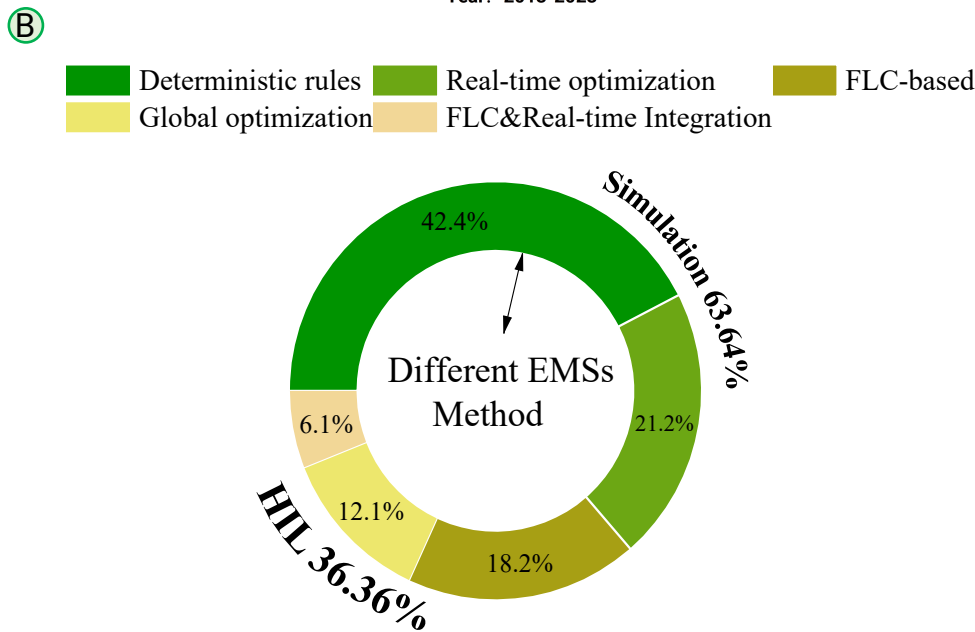
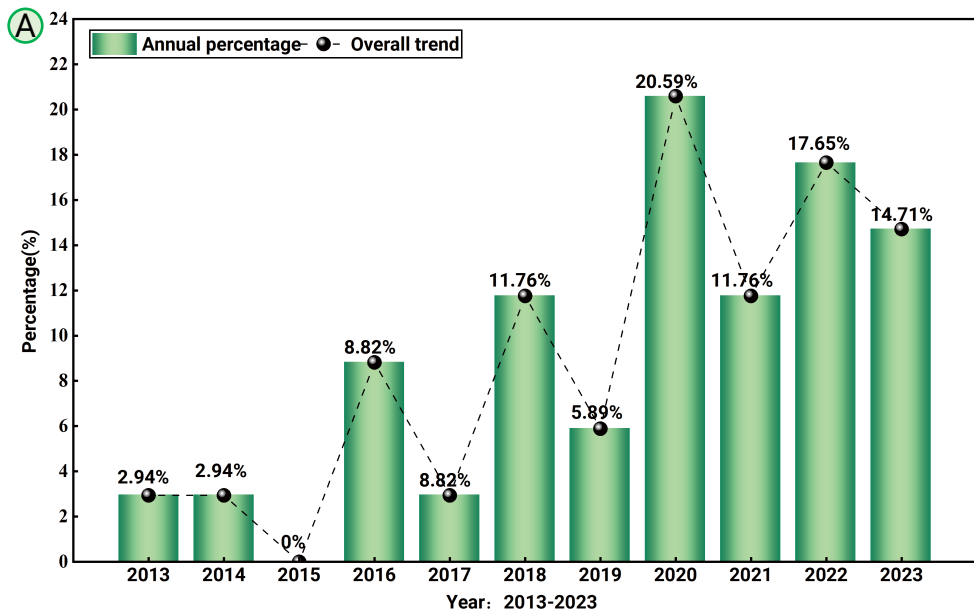
lighter tasks due to its 28-kWh battery. Due to the high cost, materials, and production processes associated with battery production, single-energy power systems are severely limited because power batteries are not always high power or high energy density. Long charging times, limited environmental adaptability, and range are further issues. Large-scale charging facilities are not feasible in rural areas due to shaky power grid infrastructure and variable power supplies. Agricultural regions are large and sparsely populated, which makes widespread charging stations necessary and raises the cost of infrastructure. The efficiency of charging facilities is further challenged by seasonal and periodic fluctuations in the demand for electricity. Furthermore, the less convenient distribution of maintenance resources in rural regions relative to urban areas makes it more difficult to maintain these facilities.

New energy, such as photovoltaics (PV), are increasingly integrated into agricultural tractors. In a grid-connected setup (Figure 6E),³⁶ the battery can be charged by the grid when the PV system is insufficient, ensuring a stable power supply. In the off-grid structure (Figure 6F), the PV array serves as the sole charging source, ideal for field operations where grid access is limited. During fieldwork, the PV system provides auxiliary charging, extending the operational range and reducing dependence on traditional power sources. Figure 6G depicts solar tractors with onboard PV systems.⁴⁰ Despite the advantages, integrating PV panels may impose limitations regarding size, space, weight, and cost, potentially reducing the tractor's operational flexibility due to increased weight.

Diesel-Electric hybrid powertrain (DEHP)

As a bridge between fuel power and pure electric power, the Diesel-Electric Hybrid Powertrain (DEHP) is normally composed of an electric motor (EM) and an internal combustion engine.⁴¹ An analysis of comparisons in Ref. [42] revealed that the fuel efficiency of DEHP was 18% higher than that of conventional fuel-powered systems at the same soil depths and plowing conditions. Based on the distribution of the engine and motor, DEHPs can be divided into series, parallel, and series-parallel configurations.⁴³ The mechanical and electrical pathways are arranged in series and parallel, respectively, in these configurations. Complex, split-parallel, and power-split configurations are examples of variations on the series-parallel topology, as shown in Figure 7A.





Series hybrid configurations are well-suited for fuel-saving and emission reduction due to their precise control and long operating life. For example, Ref. [44] introduces a series topology that combines an electric motor with a mechanical transmission to simplify the traditional multi-gear transmission system. However, it suffers from energy losses during multiple conversions and relies solely on electric propulsion. Parallel hybrid configurations combine mechanical and electric propulsion, offering multiple working modes.⁴⁵ The system can optimize component sizing, allowing for a smaller drivetrain and motor. However, it requires complex rules for torque and power distribution, adding mechanical links and making dynamic state switching challenging. Ref. [46] designed a parallel hybrid model with a 50-kW engine and a 9-kW motor, achieving an 11.78% fuel efficiency improvement compared to conventional tractors. The series-parallel hybrid configuration provides greater control flexibility and more operating modes, but also involves increased system complexity and construction costs.⁴⁷ Additionally, tractors require power transmission for implementation, complicating the integration of such systems. Therefore, this structure is not discussed in detail here. Table S1 provides a comparative analysis of the three DEHP configurations.

Figure 4. Trends and Methods in Driveline and EMS Research for ETs (A) Annual trends (2013–2023), (B) Research and validation methods.

Hybrid energy source system (HESS)

As shown in Figure 7B, typically, the structure of a HESS includes a power conversion device, a high-power density element (HPDE)⁴⁹ and a high energy density element (HEDE).^{48,50} Together, these two factors enhance the flexibility and stability of the power system.^{51–52} HESS structures are classified as passive, semi-active, or active topologies depending on how power conversion components and energy storage elements are combined.^{53–54} Table S2 offers an in-depth analysis of the three HESS topologies.

The passive topology is the simplest configuration as it does not require a DC/DC converter, making it compact and cost-effective.^{55–56} In this setup, HEDE and HPDE are connected in parallel to the DC bus, aligning the composite power supply voltage with the DC bus voltage. HPDE acts as a low-pass filter, improving capacity and filtering performance. However, maintaining consistent voltage is challenging due to significant fluctuations in HPDE voltage during discharge, which affects bus stability.⁵⁷ Additionally, the HESS voltage must precisely match the bus voltage.^{58,59} Without power regulation, HEDE discharges irrespective of HPDE's state, reducing the energy storage lifespan. The semi-active topology extends the passive design by using DC/DC converters to regulate HEDE output, ensuring steady current and high output.⁶⁰ However, the broad voltage range of HPDE may cause bus voltage fluctuations, necessitating increased HPDE capacity, which raises costs.⁶¹ In the HPDE-dominant structure, HPDE is connected to a DC/DC converter, providing more control but also increasing complexity and cost. Active topology, in which each energy storage element is connected to a separate DC/DC converter, allows for bidirectional power and voltage control.⁶² This setup provides flexibility and extends the cycle life of storage elements through control algorithms.⁶³ However, managing two energy storage components increases structural dimensions, system costs, and complexity in the EMS.

OVERVIEW OF CONTROL APPROACHES FOR POWER AND PROPULSION SYSTEMS

In contrast to electric vehicles, tractors are large agricultural machines that require the carrying of various implements in order to carry out a variety of agricultural tasks, including harvesting crops, rotary plowing, pear plowing, pesticide spraying, and so forth. Consequently, the power system must not only accomplish the driving task but also distribute power in accordance with the power level of agricultural tasks, as illustrated in Figure 8. The current definition of EMSs is preferred for the purposes of this review. This section describes the different control strategies for controlling ETs' propulsion and power systems under various load scenarios.

Rule-based control strategy

A set of logical rules that computers can understand is produced by rule-

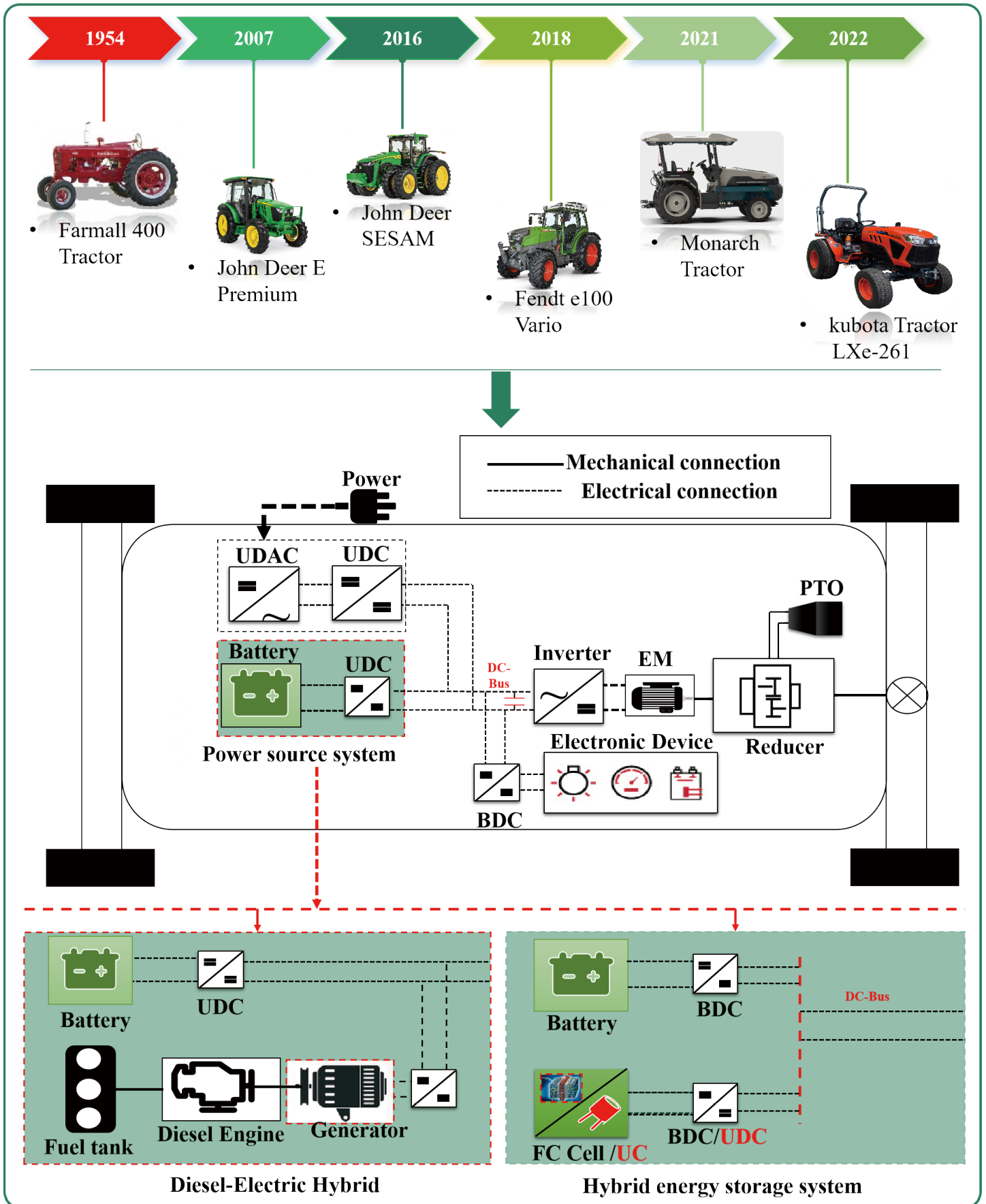


Figure 5. Development Timeline of Hybrid Agricultural Tractors (1954-2022).

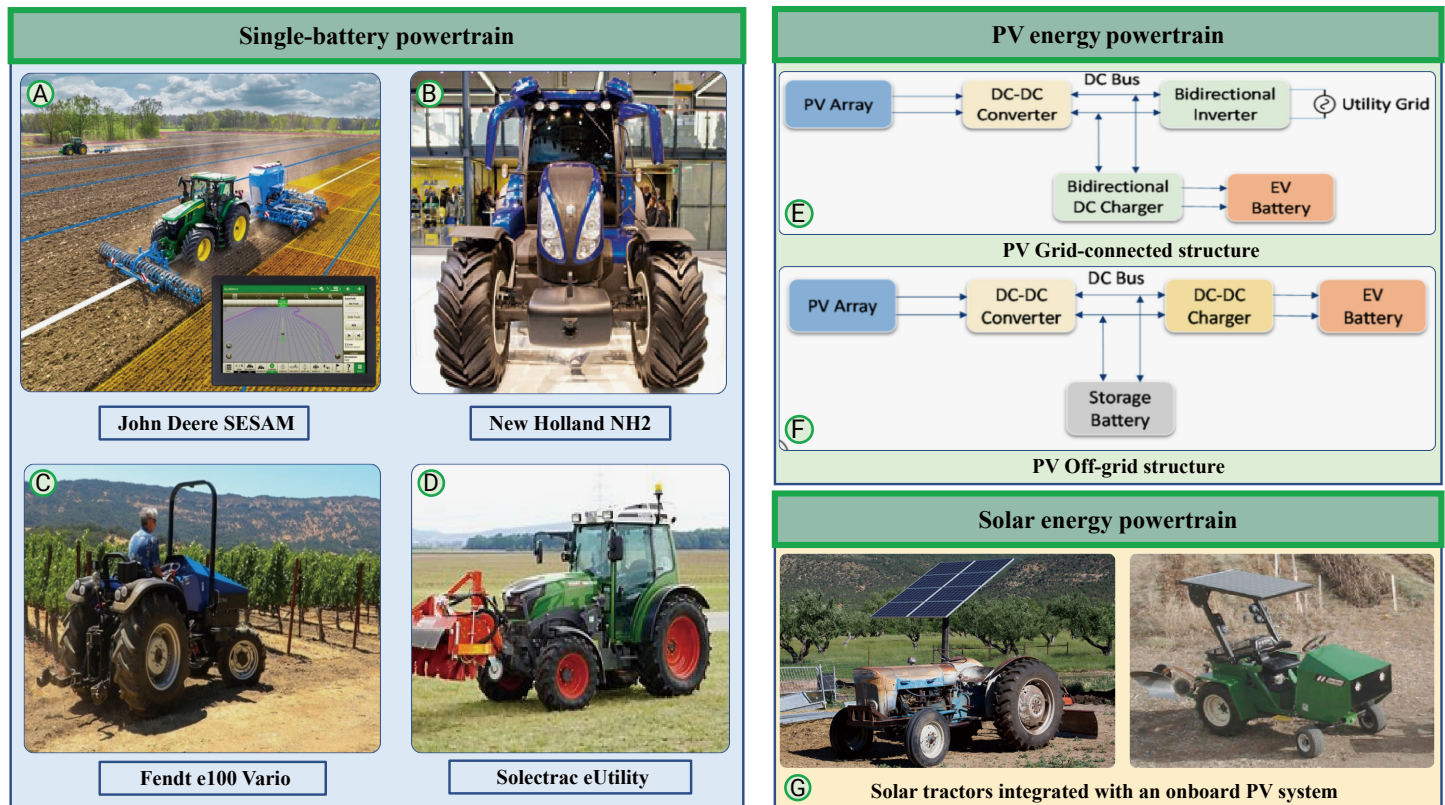


Figure 6. Single-energy powertrain agricultural Tractors.

based control techniques from engineering knowledge, numerical models, or experimental data.^{64,65} These methods include both Deterministic Rule-Based Energy Management Systems (RB-EMSs) and Fuzzy Logic EMSs.^{66,67}

Deterministic RB-EMSs. Establishing output variable values based on the driver's state and system inputs, deterministic RB-EMSs guarantee power demand fulfillment by allocating power under ideal operating conditions or within a high-efficiency region.⁶⁸ These RB-EMSs follow prearranged rules based on engineering experience.^{69,70} Frequency decoupling control (FDC) EMSs, power following strategy (PFC) EMSs, and thermostatic control (TC) EMSs are examples of common deterministic rule-based EMSs.^{71,72} Ref. [78] compares the TC and PFC strategies for ET. TC effectively manages engine operation and energy storage, optimizing fuel consumption and emissions, but it causes frequent switching for batteries and deep battery discharge. PFC improves overall system efficiency and battery durability compared to TC but cannot meet load power demands under all conditions.⁷⁹

Modern fuel-powered and battery combinations have been gradually replaced by a variety of HESSs.⁸³ Therefore, frequency filtering has been used to enhance Deterministic RB-EMSs. The low-pass filter (LPF) separates the total load current into high-frequency and low-frequency currents.⁸⁴ Supplementing the HEDE with low-frequency current results in a steady-state power output, while the HPDE receives the high-frequency current signal for high-power output. The SimMet, Haar, and Daubechies filters are examples of common low-pass filters. Due to their good time-domain tightness, which allows for quick computation, Haar filters are one of the most popular among them in EMS. Table S3 compares the EMSs for ETs that are based on Rule-based control strategy.

Fuzzy Logic EMS. Fuzzy Logic Control (FLC) addresses uncertainty and ambiguity by emulating human decision-making processes. It is particularly effective in managing complex, nonlinear, and multivariable systems that are challenging to model with precision. FLC employs "if-then" rules to establish relationships between inputs and outputs, enabling real-time control actions during system operation.^{88,89} However, its ability to guarantee optimal solutions is constrained by the reliance on fuzzy rules derived from engineering expertise and practical experience. Additionally, manually adjusted parameters can lead to suboptimal or partial solutions.⁹⁰ Enhancing EMS perfor-

mance necessitates precise determination of fuzzy parameters, such as the width and center of membership functions, to improve control accuracy.⁹¹

Table S4 compares the EMSs for ETs that are based on FLCs. Ref. [92] created an FLC-based DEHP EMS by using tractor demand power and battery SOC as input variables, the method greatly improved fuel efficiency during plowing operations and ensured smoother battery SOC curves. However, the comprehensive analysis of energy distribution is limited by ignoring important factors such as dynamic changes in plowing traction. Ref. [93] proposed a dynamic torque distribution strategy between the internal combustion engine and electric motor, with the vehicle's demand torque and the battery pack's SOC as key input variables. This approach enabled precise control over the battery's SOC, contributing to improved engine fuel efficiency. However, challenges were encountered, particularly related to the fuzzy controller's modeling complexity and computational demands. Furthermore, critical factors such as the tractor's operational conditions and external environmental influences were not adequately considered, limiting the method's practical applicability in real-world agricultural settings.⁹⁴ In Refs. [95,96], a hybrid powertrain integrating supercapacitors, fuel cells, and batteries was designed. The powertrain utilized an EMS based on FLC. The input variables included the motor's power demand and the SOC of the storage elements, while the output variable was the proportionality factor determining the contribution of the battery pack to the total power supplied by the dual powertrain. Compared to rule-based EMSs, this approach significantly reduces overall system variability and improves efficiency. However, the HESS is governed by the Rule-Based EMSs, which employ predetermined rules, typically derived from expertise and mathematical modeling. Commands are communicated to the HESS by the Rule-Based through a network, which introduces the risk of communication delays and single points of failure, potentially degrading the performance of the control system.⁹⁷

Optimization-based control strategy

When it comes to optimization-based EMSs, the choice of the objective function is contingent upon the demands of system performance, such as the need to maximize battery cycle life or minimize overall energy losses.⁹⁸

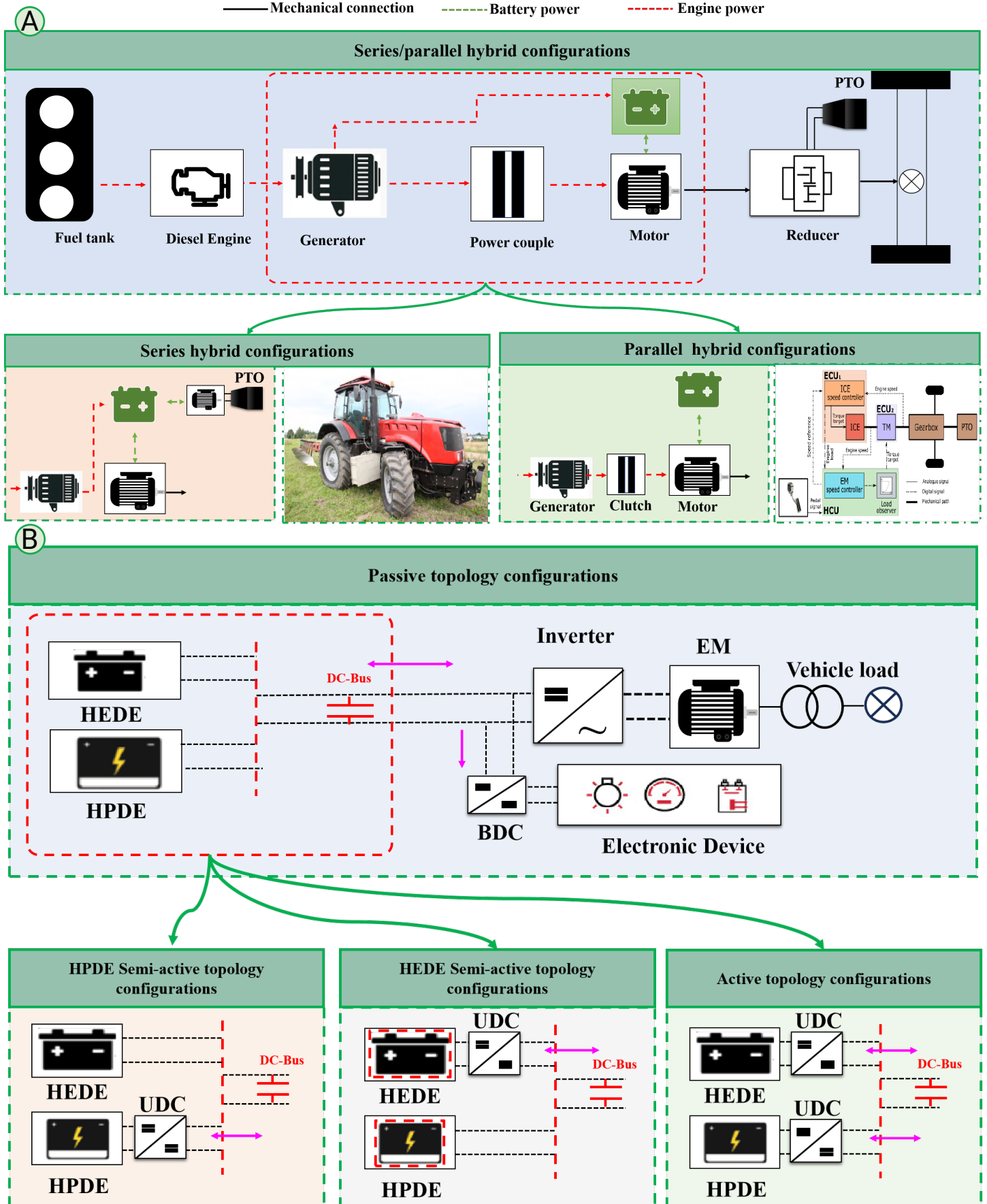


Figure 7. The structure topology for hybrid systems Diesel-Electric hybrid powertrain.

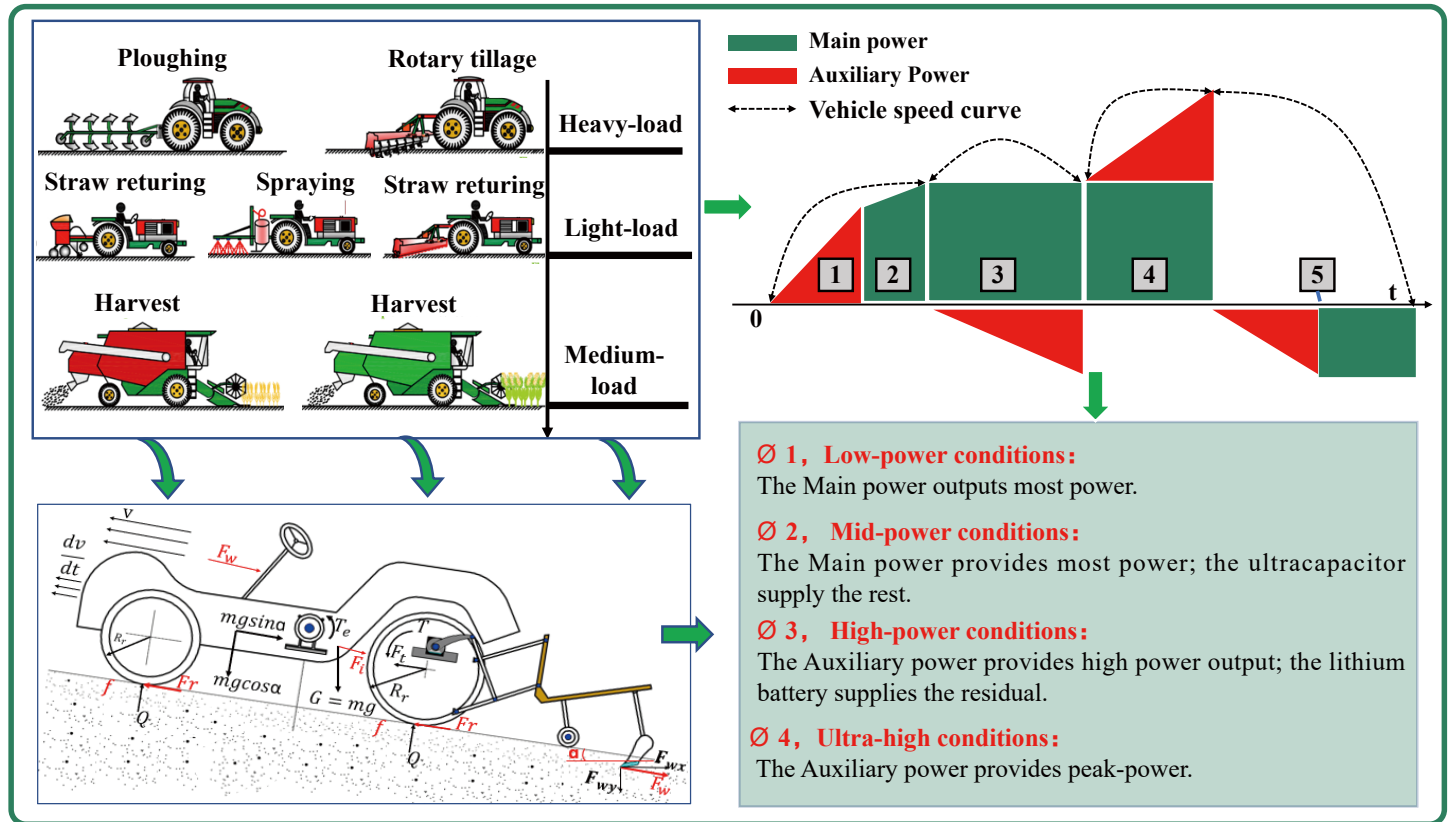


Figure 8. Analysis of Tractor Field Operations.

After that, an optimization technique is used to identify the best answer, which establishes the system's ideal power distribution.⁹⁹ The methods based on optimization are classified into two categories: global and real-time strategies, depending on the kind of information gathered.¹⁰⁰

Global-based optimization. Global optimization is an offline optimization strategy that aims to obtain the optimal solution by leveraging previous information obtained during the operation cycle.¹⁰¹ By leveraging this prior information, global optimization algorithms achieve near-optimal performance.¹⁰² However, due to their high computational complexity, these algorithms are not suitable for real-time operation. Nevertheless, global optimization is often used as a benchmark strategy to evaluate and compare other improved optimization strategies.¹⁰³ The main optimization algorithms include dynamic programming (DP), stochastic dynamic programming (SDP), minimum value theory algorithms and model predictive control (MPC), etc.¹⁰⁴

Dynamic Programming (DP) and Model Predictive Control (MPC) are widely used global optimization methods.¹⁰⁵⁻¹⁰⁷ Ref. [108] utilized Dynamic Programming to optimize engine power output and battery State of Charge (SOC). DP systematically explores all possible control trajectories to identify the optimal energy allocation that minimizes fuel consumption over a specified time horizon. While effective in offline optimization for reducing fuel consumption and improving battery utilization compared to Predictive Functional Control (PFC), DP requires high SOC discretization to accurately capture dynamic changes, which increases interpolation calculations and leads to exponentially growing computation times as state and control variables increase.¹⁰⁹⁻¹¹⁰ Stochastic Dynamic Programming (SDP) is an extension of the Dynamic Programming (DP) algorithm, incorporating random processes to handle uncertainties using statistical data, such as real-time operating cycles.¹¹¹ The quality of these random processes significantly affects the optimal solution. In SDP, uncertain operating conditions are represented by a Markov chain. For instance, Ref. [112] developed a real-time adaptive EMS using SDP combined with an extreme value search algorithm to address the unpredictability in DP-based EMSs for HESS. This approach effectively mitigated peak loads on the power battery, reducing the depth of discharge (DoD) and minimizing the frequency of high-current events,

thereby extending the battery lifespan. Additionally, it optimized the energy distribution between the power battery and the supercapacitor, allowing the supercapacitor to handle rapid load fluctuations and regenerative braking, thus enhancing overall energy utilization efficiency. However, it relies on extracting the state transition matrix from historical data, which introduces high computational and storage demands, making real-time energy allocation challenging due to the difficulty in obtaining accurate state transition functions.¹¹³

For real-time applications, the MPC can be used without requiring full driving cycle information because it combines instantaneous and global optimization techniques.¹¹⁴ By creating a predictive model, minimizing the cost function, and revising control strategies based on fresh measurements, it makes use of a rolling optimization mechanism. Take Ref. [115] as an example, to maximize fuel efficiency and preserve battery state of charge, an MPC approach was created for hybrid ETs. The ICE's built-in speed controller is integrated into the plan. Test findings demonstrated fuel savings of 12.6% in transportation cycles and 50.4% in farming activities while maintaining speed tracking. But real-time applications might find it difficult to use this method because it demands a lot of computational power and accurate modeling.

Table S5 provides a key analysis of EMSs based on Global-based for ETs. These methods typically achieve multi-objective optimization of power distribution systems, including energy consumption, operating costs, and investment costs. However, as the number of optimization goals increases, so do the constraints, which significantly increases the computational burden on the controller.¹¹⁶ Additionally, these methods require precise mathematical modeling of the system, as inaccuracies in the model can reduce the accuracy of the optimization results.

Real-time optimization. To produce a sequence of instantaneous optimal results, real-time optimization (RTO)-based EMSs seek to translate the global optimal control problem into a set of real-time optimizations.^{117,128} Despite being less than ideal, these outcomes considerably lessen computational complexity. Pontryagin's Minimum Principle (PMP), Equivalent Consumption Minimization Strategies (ECMS), Model Predictive Control (MPC), and intelligent optimization algorithms like Genetic Algorithm (GA) and Particle Swarm

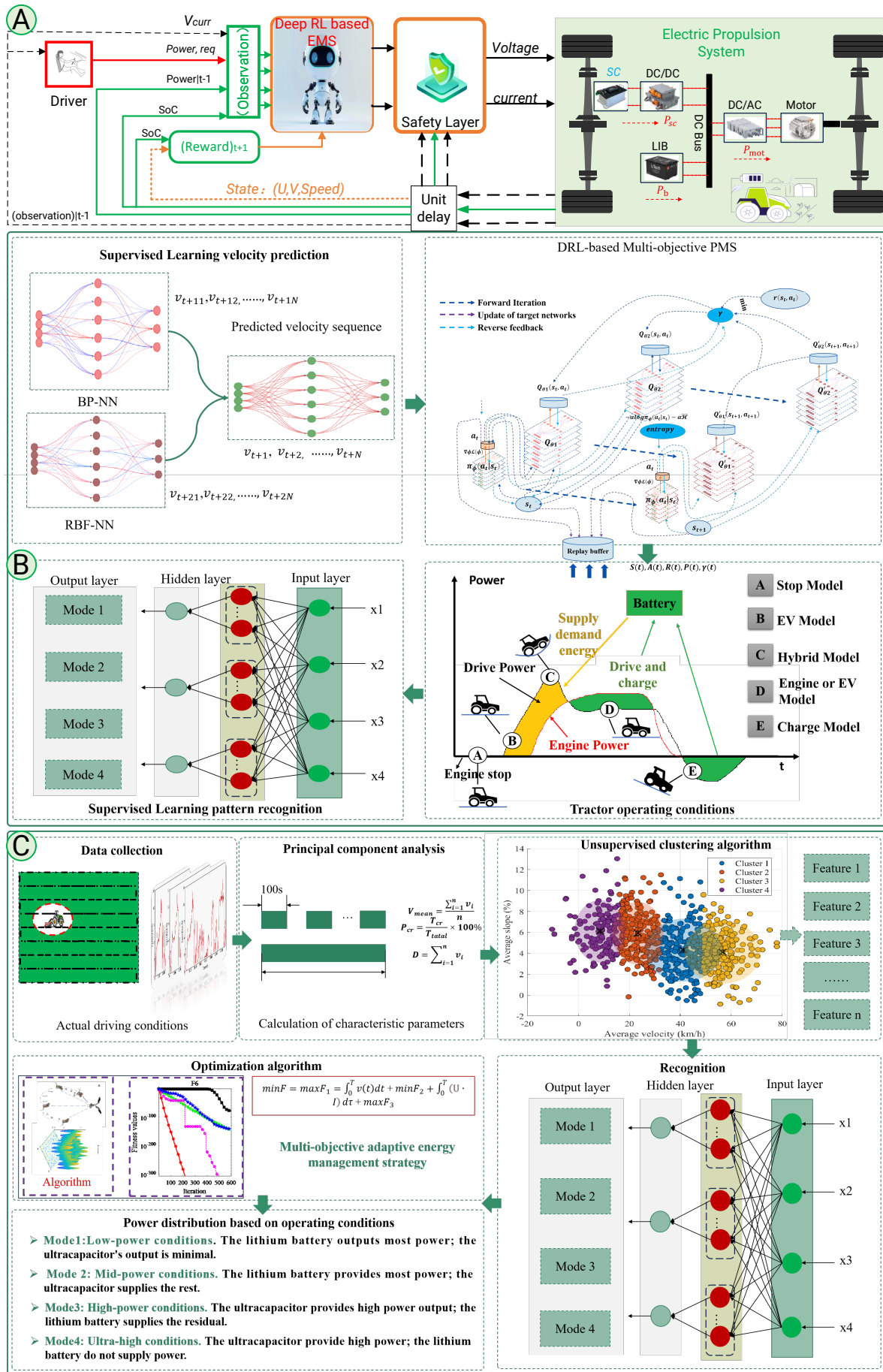
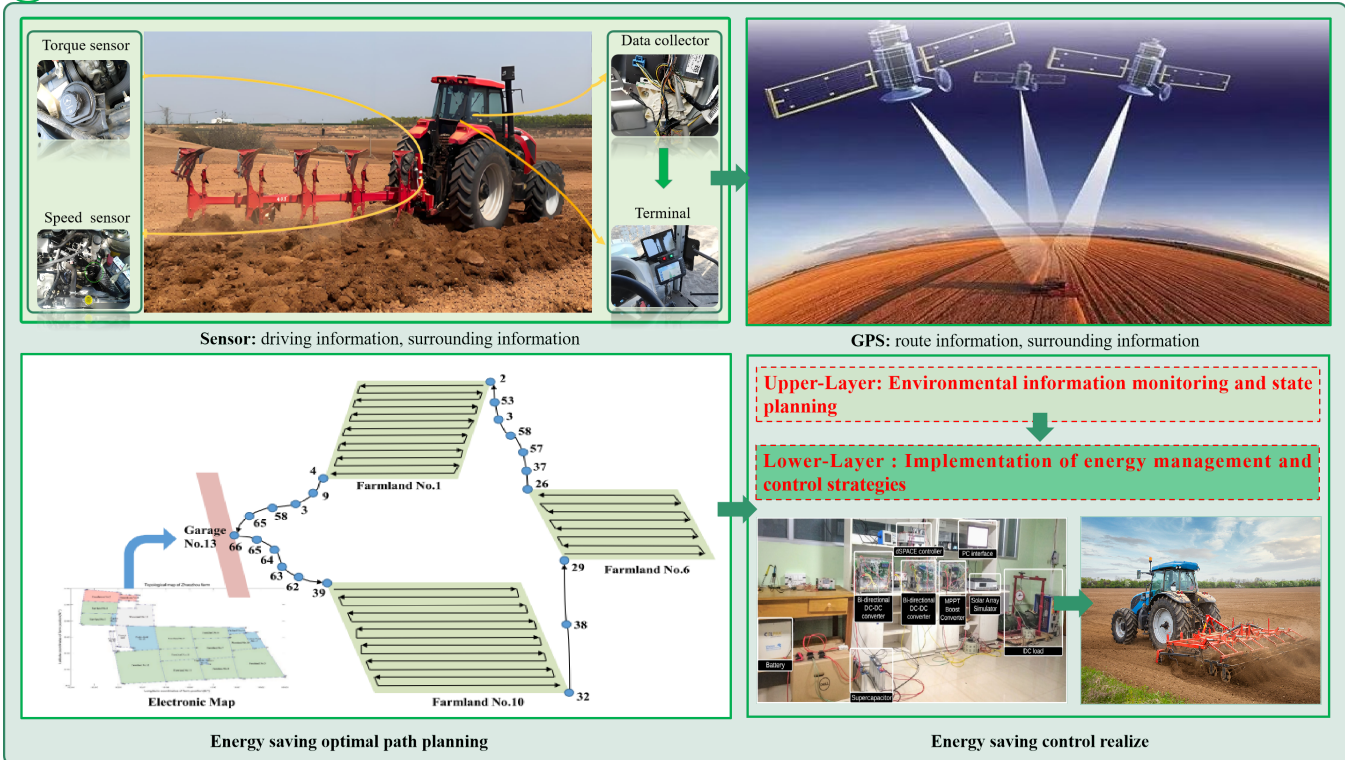


Figure 9. Learning-based control strategy (A) Reinforcement Learning-Based EMS, (B)Supervised -Based EMS, (C) Unsupervised Learning-Based EMS.

A



B

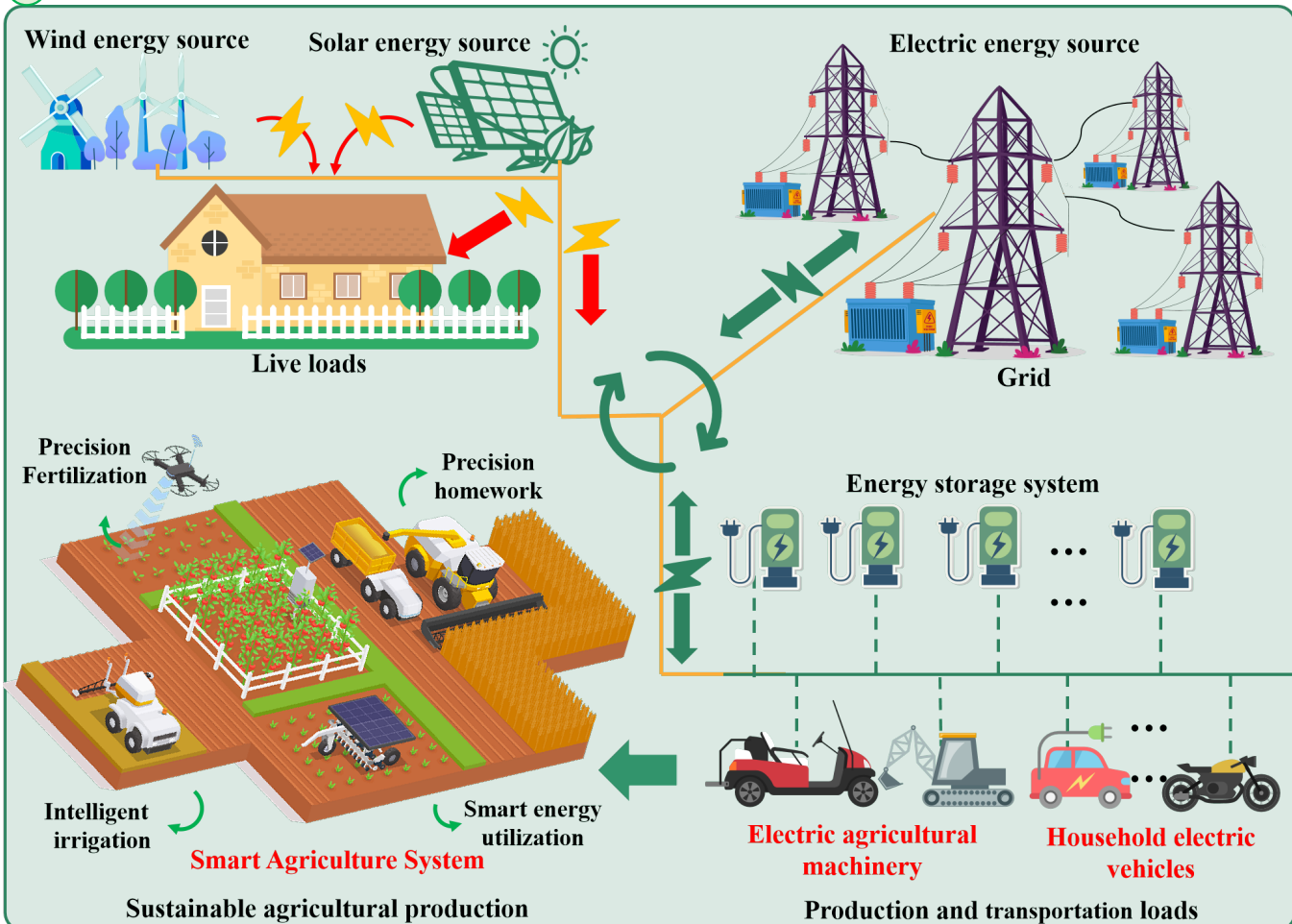


Figure 10. Collaborative Integration of smart agriculture and sustainable agriculture.

Optimization (PSO) are some of the optimization algorithms for real-time EMSs.

ECMS, as a real-time optimization technique based on PMP, aims to conserve fuel by converting electric energy usage into equivalent fuel consumption using an equivalency factor.^{118,119} Ref. [120] explains how ECMS optimizes power distribution between the engine and motor in DEHP tractors, enabling real-time torque distribution to reduce fuel consumption. However, the use of an empirically determined equivalency factor makes ECMS sensitive to varying operating conditions, limiting its robustness. Ref. [121] tested an ECMS-based EMS for a parallel hybrid tractor, achieving an average fuel saving of 14% with speed tracking, consistent with simulation results. Ref. [122] introduced a Fuzzy Adaptive ECMS (FA-ECMS) that employs a fuzzy PI controller to dynamically adjust the equivalency factor, enhancing adaptability to changing conditions and improving engine efficiency. Despite these improvements, FA-ECMS still struggles with the trade-off between load prediction accuracy and real-time performance, as the complexity of fuzzy adaptation can hinder timely energy allocation.

Swarm optimization algorithms are increasingly employed in EMS to leverage natural swarm dynamics for finding optimal solutions.¹²³ These algorithms work alongside other control methods to iteratively determine ideal parameters for objectives like fuel economy and cost reduction. Ref. [124] used Genetic Algorithms (GA) to optimize equivalency factors in ECMS, achieving an 8% reduction in fuel consumption under varying mileage and SOC conditions. In Ref. [125], a GA-optimized EMS for a hybrid tractor with a biofuel engine, photovoltaics, and batteries reduced fuel consumption by 17% compared to DP-based methods, using a two-layer approach: identifying operating conditions and optimizing energy distribution with fuzzy logic. Similarly, Ref. [126] used Particle Swarm Optimization (PSO) to optimize a fuzzy logic EMS for a horticultural electric tractor with HESS, effectively improving power smoothing and extending battery life. Furthermore, path optimization provides novel approaches to energy distribution and optimization. In Ref. [127], an Improved Whale Optimized ACO (IWOA-ACO)-based multi-node path planning algorithm was proposed to further optimize energy consumption from the path planning perspective. In flat environments, this method decreased ET energy consumption by 0.61%, and in rugged environments, it decreased by 4.32%. However, the method's extensive use in real-world situations might be constrained by its high requirement for parameter tuning and computational complexity.

Table S6, RTO-based EMSs for ET are critically analyzed. These techniques seek to increase efficiency, prolong battery life, and optimize energy management. They are all dependent on intricate optimization algorithms and confront difficulties with computational complexity and model accuracy. Variations are observed in terms of their flexibility and complexity of implementation. For example, FA-ECMS and PSO-optimized FLC EMS offer greater adaptability but are more difficult to implement, while ECMS is sensitive to operating conditions.

Learning-based control strategy

Rather than requiring explicit programming, learning-based algorithms leverage training data to enable computers to execute arbitrary tasks.¹²⁸ Its real-time data autonomous learning and self-optimization features have made it a popular choice in the electric vehicle industry in recent years. As of right now, machine learning can be divided into four categories: unsupervised learning (UL), semi-supervised learning (SSL), reinforcement learning (RL), and supervised learning (SL), as shown in Figure 9.¹²⁹

Reinforcement learning. Reinforcement learning (RL) is a widely used approach for learning-based EMSs. It stands out for its method of teaching agents' optimal actions through exploration and experimentation, rather than following predefined instructions.¹³⁰ As shown in Figure 9A, this process enables agents to identify which actions yield the highest rewards based on their interactions with the environment. RL does not require a predefined model, enabling agents to interact with their surroundings directly and adjust as a result of their actions.¹³¹ This model-free method is crucial for addressing real-time implementation challenges in EMSs because it gets around the drawbacks of depending solely on engineering experience and past knowledge of driving cycles.¹³²

EMSs are increasingly incorporating various RL techniques, such as Q-

learning and Temporal Difference (TD) learning, often enhanced with Dyna-style frameworks. Among these, Q-learning is the most widely adopted algorithm. In hybrid vehicle applications, Deep Reinforcement Learning (DRL) algorithms are particularly prominent, with techniques like Deep Q-Network (DQN), Double DQN (DDQN), Deterministic Policy Gradient (DPG), and Deep Deterministic Policy Gradient (DDPG) being actively utilized.¹³³ Ref. [134] uses a Markov Decision Process for modeling an EMS based on a Deep Q-network (DQN), utilizing state variables like engine power, battery state of charge, acceleration, and vehicle speed for power allocation. The DQN continuously adjusts engine power output to minimize fuel consumption while learning optimal policies through experience. However, due to the complexity of DQN training and the high computational demand, real-time implementation is challenging.¹³⁵⁻¹³⁶ To reduce overestimation, Ref. [137] introduces Double DQN (DDQN) in the EMS for series hybrid tracked vehicles. DDQN uses two separate Q-value networks: one to select actions and another to evaluate their value. This reduces the overestimation bias found in DQN, leading to improved stability and reduced computational complexity. Despite these improvements, DDQN can still struggle with training efficiency and convergence, especially in environments with high-dimensional state and action spaces.¹³⁸ Q-learning is a model-free reinforcement learning algorithm for finding optimal policies in finite Markov decision processes.¹³⁹ It learns action-state values stored in a Q-table, allowing the agent to select actions that maximize expected rewards through exploration and exploitation.¹⁴⁰ Compared to DQN and DDQN, Q-learning is simpler, requires less computational power, and is faster to train, making it suitable for resource-limited environments. For instance, Ref. [141] used Q-learning for an adaptive EMS in DEHP, improving adaptability and reducing computation time. However, its discrete nature limits effectiveness in continuous action spaces, potentially leading to suboptimal outcomes in complex controls. Ref. [142] applied Q-learning to power distribution in plug-in hybrids, achieving a 16.8% reduction in energy losses. Despite its simplicity and real-time control advantages, Q-learning's limitation in handling continuous actions reduces its optimization effectiveness.¹⁴³

A critical analysis of RL-based EMSs is provided in Table S7. RL requires hyperparameter tuning, which often involves multiple iterations and resource-intensive computations to achieve optimal performance.¹⁴⁴⁻¹⁴⁵ Additionally, RL models are highly sensitive to hyperparameter settings and can easily encounter the curse of dimensionality during the solving process. Improper setting of the penalty function can also affect model performance.^{128,146} Moreover, the black-box nature of RL models, with their complexity and lack of interpretability, poses limitations for engineering applications. Therefore, DRL models based on online adaptive hyperparameter search has become an important development trend.¹⁴⁷ This approach allows for the adaptive adjustment of hyperparameter combinations during training, avoiding the limitations of always using a fixed set of parameters.

Supervised learning. Supervised Learning (SL) trains an optimal control model using predefined features and target data, aiming for predictive and classification capabilities.¹⁴⁸ Algorithms like Support Vector Machine (SVM), Decision Tree (DT), or artificial neural network (ANN) are used to train the model to learn the mapping between input features and optimal energy decisions.¹⁴⁹⁻¹⁵⁰ The trained model then predicts optimal energy decisions based on the current system state.

Figure 9B illustrates an SL-based EMS framework. Historical velocity data is used in ensemble learning methods, such as Back Propagation Neural Network (BP-NN) and Radial Basis Function Neural Network (RBF-NN), to predict future velocities.¹⁵¹ This predicted velocity sequence informs an MPC-based EMS, which optimizes torque and power distribution. A driving pattern adaptive reference SOC is determined using typical driving patterns and learning vector quantization, further enhancing the system's efficiency. Currently, Support Vector Machine (SVM) is one of the most commonly used supervised learning methods.¹⁵² SVM can be combined with meta-heuristics such as Genetic Algorithms (GA) and PSO to form GA-SVM and PSO-SVM methods for driving pattern recognition.¹⁵³⁻¹⁵⁵ By extracting parameters using these algorithms and trained SVM models, driving cycles can be identified and classified to determine real-time driving conditions.¹⁵⁶

For example, in Ref. [157], an SVM-based EMS was developed to estimate the upcoming travel cycle of the vehicle and adjust the power allocation

between the engine and the motor accordingly. The results show that the SVM-based EMS significantly improves fuel economy compared to rule-based techniques. In Ref. [158], a least squares support vector machine (LSSVM)-based controller for plug-in hybrid vehicles was developed to quickly generate optimal strategies for various driving scenarios. The results indicate that the data-driven controller effectively translates global optimization knowledge into real-time control strategies, resulting in superior control performance.

Unsupervised learning. Finding latent patterns or group data in the exploratory data analysis stage is the primary purpose of Unsupervised Learning (UL).¹⁵⁹ As shown in Figure 9C, UL is mostly used to classify the driving cycle or to reduce the dimensionality of the data in order to facilitate the design of an effective control strategy in the field of vehicle energy management.¹⁶⁰ Dimensionality reduction, association, and clustering are three main goals for unsupervised learning.¹⁶¹

For Unsupervised learning-based EMSs, clustering algorithms are less prevalent compared to supervised learning (SL) and reinforcement learning (RL), as it is primarily used for optimization purposes. For example, Ref. [162] gathered real-world data on electric vehicle driving cycles, extracted key driving features, and employed clustering algorithms to classify these cycles, aiming to improve the performance of the energy management system (EMS). However, clustering algorithms in this setting tend to rely heavily on historical data, making it challenging to adapt to rapidly evolving and complex driving conditions in real time. In a similar vein, Ref. [163] used clustering algorithms to group driving conditions based on vehicle speed and battery SOC variations, which enabled more efficient energy distribution under varying operational scenarios.

Nonetheless, this approach, while effective, is limited in its ability to adapt in real-time to subtle, dynamic shifts in operating conditions, potentially resulting in locally optimal rather than globally optimal energy management solutions.

CHALLENGES DISCUSSION

This section will review the current research status of powertrains and Energy Management Systems (EMSs), providing a detailed analysis of the advantages and limitations of various strategies, along with recommendations for future research directions.

Challenges for Powertrain Advancements

Existing literature suggests that batteries are a major focus of power systems and their EMSs.¹⁶⁴ However, given the high-power requirements of agricultural operations, relying exclusively on batteries is frequently impracticable. Rapid charging and a good range are necessary for prolonged field-work. Agricultural settings can also experience significant temperature fluctuations, and batteries have a restricted operating temperature range that affects how well they discharge and store energy.

In agricultural machinery, the limitations of single-energy power systems reduce their viability. Dual-energy hybrid powertrains (DEHPs) and hybrid energy storage systems (HESSs) emerge as promising solutions to mitigate energy challenges and enhance powertrain performance. DEHPs serve as a transitional technology between conventional fuel-powered and fully electric systems, providing a balanced approach. However, they face challenges such as high integration costs and safety risks, particularly from elevated engine compartment temperatures, which can adversely affect battery performance and lifespan.¹⁶⁵ HESSs, on the other hand, integrate high-power-density and high-energy-density storage components, making them particularly suitable for renewable energy applications and operation in extreme cold climates.¹⁶⁶ Despite these advantages, their non-linear behavior and sensitivity to noise and temperature pose significant challenges for accurate state monitoring. Misjudgment of these conditions can result in deep discharges, undermining system durability and performance.¹⁶⁷ Furthermore, the incorporation of multiple storage elements increases the complexity of vehicle design, installation, and costs, potentially resulting in overly large powertrains.

The comparison of different dynamic systems in terms of dynamic performance, cruising ability, economic efficiency, charge efficiency, and emission performance is provided in Table S8.

Challenges for Energy Management Strategies

EMSs face significant challenges in achieving operational efficiency and effectiveness. Rule-based techniques are favored for their simplicity and real-time performance, particularly in contexts with established expert knowledge.^{168,169} However, their reliance on static, expert-defined rules limits their optimization capacity, rendering them inflexible and less scalable in dynamic environments. Optimization-based strategies, including real-time and global optimization, offer unique advantages but also face limitations. Globally optimized techniques can handle comprehensive optimization tasks but suffer from the "Dimensionality Curse" leading to high data and computational demands that reduce real-time applicability in dynamic scenarios.^{101,128,170} Real-time optimization methods, while offering good real-time performance, often require complex implementations to manage dynamic models effectively.¹⁷¹ Learning-based approaches promise robustness and strong real-time performance but come with high computational demands and complexity.^{128,172} Additionally, their performance is highly dependent on the availability of high-quality, large-scale training datasets and an advanced understanding of data dynamics. Moreover, effective real-time adaptation necessitates extensive expertise and continuous refinement. Table S9 summarizes the strengths and limitations of these EMS approaches, providing a comprehensive comparison of their respective advantages and challenges.

Challenges in the Application of Control Methods

Software-in-the-loop (SIL) simulations are utilized to verify the viability of EMSs.¹⁷³ Even though SIL simulations are more cost-effective and safer, their dependability is typically lower.¹⁷⁴ With multiple objectives and constraints, EMSs poses a challenging optimization problem. The complexity of the involved power systems requires precise system modeling to achieve optimal outcomes, which may, in turn, lead to concerns about the validity and reliability of simulation results. While data-driven models have the potential to increase accuracy, a significant quantity of high-quality data is necessary for their operation.¹⁷⁵ System modeling errors can be efficiently addressed by hardware-in-the-loop (HIL) simulation platforms, resulting in increased reliability.¹⁷⁶ All-scale simulation platforms, however, are too expensive and space-consuming for experimental research. A feasible approach is to create a small-scale semi-physical platform that combines SIL and HIL tests.¹⁷⁷ Designing an efficient conversion model ensures that data from simulations accurately reflects real-world conditions, enhancing control strategy viability. Data-driven powertrain modeling, informed by agricultural field data, produces accurate ET operation models. Using equivalent modeling, this data is converted into parameters, which are then used to optimize control laws for optimal power distribution, creating a multi-objective adaptive EMS. This comprehensive approach significantly improves the feasibility and reliability of EMSs for ETs. Finally, by integrating real hardware with simulation models, the HIL system validates and tests strategies in a controlled environment, leveraging the advantages of both SIL and HIL simulations.

OUTLOOKS

Optimization of Power System

The electrification of agricultural machinery places stringent demands on power system optimization, especially in harsh agricultural environments. Research should focus on optimizing the motor, battery, electronic control systems and their integration. The motor system must emphasize high power density and efficiency to handle continuous high-load operation, with enhanced vibration resistance and durability to stabilize the system and reduce transient battery impacts in rugged and variable environments. The battery system, as the key energy storage unit, requires improvements in energy density, charging efficiency, and environmental adaptability, especially under extreme temperatures. Enhancing battery thermal stability and safety can be achieved by improving thermal management and optimizing materials, such as using solid-state batteries.

The electronic control system should provide intelligent control, ensuring efficient motor output, battery management, and real-time synergy across the power chain, thereby maintaining stability and efficiency in diverse working conditions. Additionally, promoting diverse electric equipment such as agricultural robots, seeders, and sprayers will further enhance agricultural

efficiency and precision through advanced path planning, intelligent navigation, and autonomous operation capabilities.

Multiple strategy optimization and intelligent information fusion

Integrating multiple algorithms can significantly improve EMS performance.^{178,179} Combining the global optimization capabilities of global algorithms, the adaptability of fuzzy logic, and the real-time response of optimization algorithms can enhance EMS efficiency, robustness, and control.¹⁸⁰ Current EMSs for ETs predominantly rely on statistical models, which often lead to inaccuracies in practical applications.^{181,182} Thus, data-driven EMS development is essential.¹⁸³ Real-time data collection, including speed, acceleration, and route information, along with data analysis and machine learning, can support the development of intelligent energy management models for ETs. Emerging multi-source information fusion technology also offers significant potential to enhance tractor power systems.^{178,184}

As shown in Figure 10A, high-precision electronic maps provide road conditions, while multi-sensor data fusion monitors field information such as tractor position, slope navigation, and obstacle avoidance. This supports path planning and optimizes parameters like speed and acceleration, contributing to efficient energy management under diverse conditions.¹⁷⁹ Intelligent network technology and cloud-vehicle communication further facilitate real-time monitoring and optimized energy control, enhancing powertrain performance and energy efficiency.

Diverse Energy Source Integration

As shown in Figure 10B, powertrains could integrate diverse energy sources like electricity, solar, and wind power. This integration enhances energy utilization efficiency. Precision agriculture techniques, such as intelligent irrigation and accurate fertilization, further improve efficiency and reduce pesticide and fertilizer use, minimizing environmental pollution. Ref. [184] highlights the potential for large-scale electric agricultural machinery (EAM) grid connections and battery-swapping technologies.

By prioritizing rural photovoltaic power and integrating surplus electricity into the grid, ETs can support peak load management within emerging power systems involving photovoltaics, wind, and grid infrastructure.¹⁸⁵⁻¹⁸⁸ Additionally, ETs can act as virtual batteries alongside other electric vehicles, optimizing spare battery use and increasing powertrain flexibility, thereby reducing initial battery investments and maximizing energy efficiency.

Practical Implications of ET Powertrains and EMSs

The implementation of ETs powertrains and EMSs offers a transformative opportunity for agriculture, policy, and sustainability. Integrating ETs with renewable energy sources, intelligent energy distribution, and seamless switching between grid and off-grid modes enhances flexibility across diverse environments. Powered by solar, wind, and advanced batteries, ETs reduce fossil fuel use, lower costs, and cut emissions. Modular system

design allows energy integration based on specific needs, while EMSs optimize energy allocation for efficiency and stability. Advanced electric equipment, such as robotic seeders, precision sprayers, and autonomous plowing systems, increases efficiency and precision, reduces labor, and minimizes environmental impact. This shift supports precision agriculture, improving resource use, reducing waste, and lowering emissions. Supportive policies, including incentives for renewable energy, battery-swapping, and smart systems, are key to accelerating ET adoption.

Additionally, encouraging rural electrification projects and integrating ETs into grid systems ensures efficient energy use and strengthens independence. ETs also reduce environmental impact by minimizing water, fertilizer, and pesticide use, mitigating soil and water pollution. The vision for ETs powertrains and EMSs is to create an intelligent, interconnected, and sustainable agricultural energy system that adapts to changing conditions while maximizing energy efficiency and productivity.

CONCLUSION

The development of powertrains and EMSs for electric tractors (ETs) presents both opportunities and challenges. The unique operational demands of agricultural environments, such as high load variability, rugged terrains, and the need for long operational endurance, require powertrains that are highly reliable, robust, and efficient. This review provides a comprehensive assessment of the current state of ET powertrain technologies and EMSs, highlighting their advantages, limitations, and prospects. The current research predominantly relies on theoretical modeling and optimization algorithms, validated primarily through software-in-the-loop (SIL) simulations. While these approaches have provided a solid foundation, they lack sufficient real-world testing, which is crucial to understanding the practical implications of ETs under harsh agricultural conditions.

Key areas that need further advancement include the development of battery technologies with enhanced range, lifespan, and thermal stability, as well as intelligent EMSs that optimize power output and efficiency while ensuring robustness under varying field conditions. Multidisciplinary approaches, combining advancements in battery materials, motor control, and intelligent control systems, are crucial to achieving these goals. Moreover, field-level testing and practical validation should be emphasized to bridge the gap between theoretical development and practical deployment.

To move forward, investments in targeted R&D, innovation in intelligent powertrain integration, and the standardization of power system reliability for agricultural machinery are essential. As ET technology continues to evolve, the integration of automation, intelligent energy management, and advanced battery solutions will lead to more efficient, precise, and sustainable agricultural practices. Ultimately, these advancements have the potential to significantly enhance agricultural productivity, reduce environmental impact, and promote the widespread adoption of electric tractors in diverse agricultural applications.

Nomenclature

AM	Agricultural Machinery	PSO	Particle Swarm Optimization
EAM	Electric Agricultural Machinery	RL	Reinforcement learning
ET	Electric Tractor	ICE	Internal Combustion Engine
EMS	Energy Management Strategy	UL	Unsupervised Learning
DEHP	Diesel-Electric Hybrid Powertrain	DRL	Deep Reinforcement Learning
HESS	Hybrid Energy Storage System	SL	Supervised Learning
BDC	Bidirectional DC Converter	SVM	Support Vector Machine
UDC	Unidirectional DC Converter	DT	Decision Tree
EM	Electric Motor	DQN	Deep Q-network
PTO	Power Take Off	ANN	Artificial Neural Network
HEDE	High Energy Density Elements	GPS	Global Positioning System

HPDE	High Power Density Elements	DDQN	Double DQN
CAESS	Compressed Air Energy Storage Element	TC	Thermostatic Control
SMESS	Superconducting Magnetic Energy Storage System	PFC	Power Following Control
FESS	Flywheel Energy Storage System	SOC	State of Charge
DP	Dynamic Programming	FLC	Fuzzy logic control
SDP	Stochastic Dynamic Programming	GA	Genetic Algorithm
ECMS	Equivalent Consumption Minimization Strategies	MPC	Model Predictive Control

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AUTHOR CONTRIBUTIONS

All authors contributed to the manuscript and approved the final version

DECLARATION OF INTERESTS

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

DATA AND CODE AVAILABILITY

Data are available from the corresponding author upon reasonable request.

SUPPLEMENTAL INFORMATION

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