
INTELLIGENT ENERGY MANAGEMENT IN AGRICULTURE: A SYSTEMATIC REVIEW OF INTERNET OF THING, RENEWABLE INTEGRATION, AND ARTIFICIAL INTELLIGENCE TECHNIQUES

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ABSTRACT

Drawing on an analysis of 85 studies in the period 2020-2026, this review examines how smart technologies are utilized for energy management in agriculture. This review uncovers current trends and future trajectories across six themes: farm energy monitoring made possible by IoT; the incorporation of renewables into agricultural operations; forecasting of energy needs for the storage and processing of crops; policy frameworks for agro-energy; the use of AI to optimise heavy-duty farming equipment; and blockchain for peer-to-peer energy trading on rural grids. Among the key findings is the capacity of AI to transform on-farm energy consumption through demand-response in livestock and irrigation facilities and a better integration of decentralised renewables in microgrids. At the same time, the study highlights several shortcomings, particularly regarding system scalability for farms of different sizes, the real-time demands of variable weather and crop cycles, and the computational limits encountered off-grid. A four-step methodology has been employed to bridge the divide between theoretical propositions and practical implementation challenges, thus providing a road map to a smart EMS that is both resilient and economical for agri-food value chains. In so doing the research puts forward a comprehensive framework for agricultural engineers, researchers and energy policymakers to build more sustainable farm energy systems and surmount the obstacles to field-level deployment that are peculiar to the rural environment.

Keywords: Demand-Side Management; Smart Farming; Renewable Energy; Artificial Intelligence; Internet of Things; Energy Forecasting; Agricultural Electrification

1. INTRODUCTION

The rapid increase in population, urbanisation, and climate change effects placed immense strain on global food systems. The world's population is estimated to reach 9 billion by 2037, with a significant proportion residing in urban centres (Gu *et al.*, 2021). A report released by the Food and Agriculture Organization (FAO) stated that there must be a significant increase in food production if this demand is to be met but this will also bring other challenges such as causing a rise in the emission of greenhouse gases (GHG), scarcity of water resources, and land degradation especially if farmers continue to use traditional farming technique (Emegha *et al.*, 2025). This has therefore warranted the need for innovative and sustainable farming methods with low environmental footprint and optimized operational efficiency.

Smart farming, which is also referred to as precision agriculture, digital farming, or Agriculture 4.0 integrates advanced technologies including the IoT, AI, robotics, and data analytics to optimise resource utilisation, increase yields, and enhance sustainability (Vardhan *et al.*, 2025). A modern smart farm consists of multiple technical fields such as precision agriculture, cyber-physical systems, and sustainable energy. The goal of smart farming is to optimise the water-energy-food nexus and includes highly mechanised, automated, and data-driven ecosystems. However, smart farming entails substantial energy consumption. About 30% of the world's energy consumption comes from activities related to the agri-food sector, and about one-third of the total GHG emissions from these systems are attributable to their energy use (Corigliano *et al.*, 2025). Energy consumption in agriculture varies substantially across production stages, with irrigation alone consuming between 12,173 and 23,781 MJ ha⁻¹. In controlled environment agriculture (CEA), particularly greenhouses, energy requirements are higher,

with lighting, heating, ventilation, and air conditioning (HVAC) systems consuming vast amounts of electricity to maintain optimal microclimatic conditions (Corigliano *et al.*, 2025).

Managing the water-energy-food nexus is a very complicated process in many developing regions, particularly in Sub-Saharan Africa. Challenges such as unstable grid, limited access to modern facilities and capital exacerbates these challenges. Some farmers therefore use diesel generators and other traditional systems to meet agricultural demands, thereby increasing operational costs and constraining productivity. The introduction of AI and other intelligent technologies offer potential solutions to these challenges and are poised to transform the agricultural sector especially in the area of energy and other resource management. These intelligent systems have the ability to process large datasets, recognize patterns, and predict future outcomes making them ideal for the complex and variable nature of agricultural activities. ML models have been widely used to forecast energy consumption, which enables better load management and scheduling of irrigation and climatic control operations. Reinforcement learning (RL) techniques have also been used to improve the optimal scheduling of microgrids and also deploy DSM response techniques. Other AI-based tools such as Artificial Neural Networks (ANN), genetic algorithms (GA), and fuzzy logic (FL) have also been used to solve optimisation problems relating to energy storage management, renewable energy integration, and load prioritization especially in smart farming (López-Pérez and Flores-Prieto, 2023).

Even with all the benefits of AI-based solutions for EMS, there are many limitations, especially when it comes to their application in the farming sector. In large scale farming, these systems can be very complex to use because there is large data to be processed from IoT sensors and smart meters. Many researchers have used EMS for many applications ranging from industrial to residential settings, but their adaptability and scalability in the farming sector are limited (Tirth *et al.*, 2023). The broad implementation of these cutting-edge farming techniques remains severely limited, not only by financial outlays for infrastructure but also by cyber threats, privacy issues, and poor rural connectivity. Farming operations are becoming more mechanised and therefore it is very important for that these challenges are solved which will enhance the use of intelligent systems in energy management especially in the farm (Zhang *et al.*, 2022). These challenges are summarized in Figure 1.1.

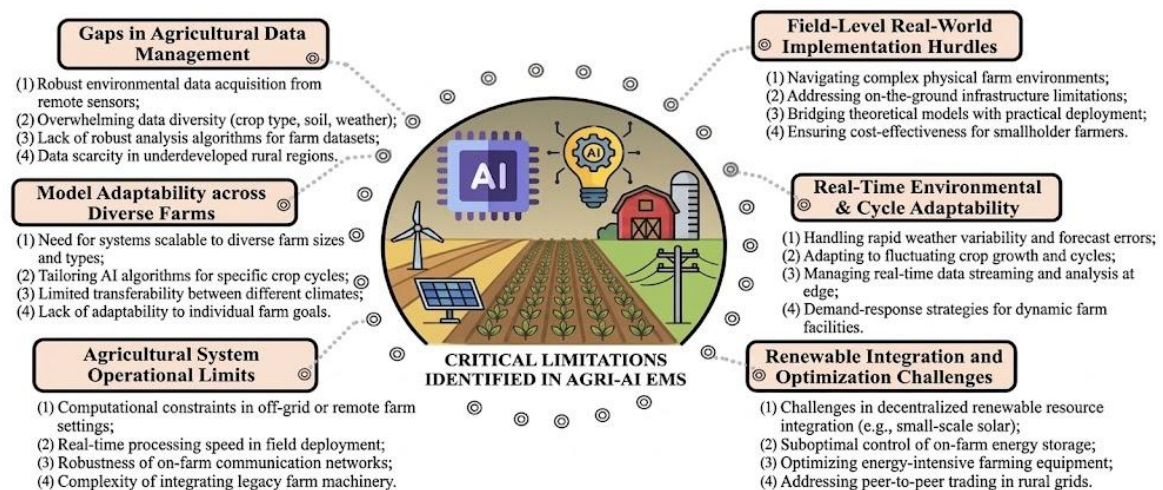


Figure 1.1: Critical Limitations Of AI-driven EMS Systems Deployed in The Agricultural Sector

This study therefore focuses on AI-driven DSM and energy management systems within the context of smart farming and agriculture by examining review papers published between 2020 and 2026. The most studied topics include irrigation optimisation, greenhouse climate control, and reinforcement learning, while scalability, blockchain applications in agriculture, and real-time adaptability remain underexplored. This review guided us to address these gaps and identify future directions for AI-driven DSM in smart farming. With a thorough analysis of what already exists in literature and their limitations, this research provides valuable insights in developing more efficient and robust EMS for applications in the agri-food sector. Figure 1.2 gives a brief overview of the strategy used in the systematic literature review which is inspired by the work done by Kim *et al.* (2021) and Rehman *et al.* (2025).

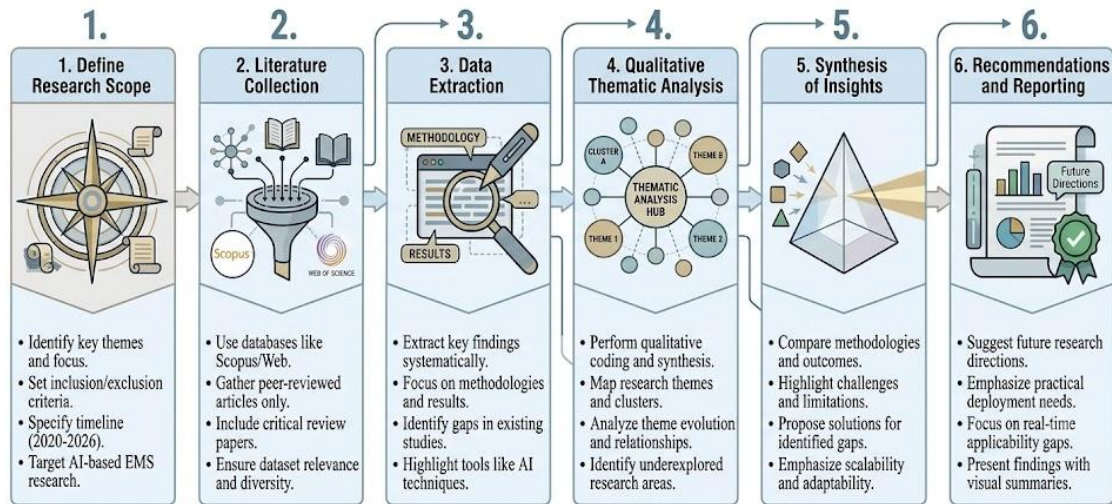


Figure 1.2: Review Strategy Adopted

1.1 Novelty of the Study

Many contributions have been given in the field of AI-driven DSM and energy management systems for smart farming from this study. With many researchers like Aguilar *et al.* (2021) focusing on the application of these technologies in smart buildings and large industries, this research focuses on the agricultural sector highlighting how intelligent energy managements systems can be applied in the entirety of smart farms from irrigation management and greenhouse climate control to renewable energy integration. This study conducts a qualitative thematic review of papers published between 2020 and 2026, which gives a more detailed and current insight into structures and trends specific to agricultural applications; bridging theoretical models with practical implementation in farming contexts.

2. RESEARCH METHODOLOGY

The methodological framework used in this research is summarised in this section.

2.1 Research Questions Formulation

To set the parameters for this review, we begin with a set of research questions (RQs) that will be put forward:

- I. RQ1: In the period from 2020 to 2026, what sub-domains in farm-level energy optimisation and DSM have been the subject of the greatest scholarly interest, as opposed to those that are left wanting in funding or attention? What can one make of such publication trends with regard to the strategic imperatives at play and the operational obstacles that endure in agricultural power management?
- II. RQ2: What role is being played by the tactical frameworks, machine-learning architectures and hybrid systems of an integrated nature in the governance of on-farm energy today, and to what extent they are able to put an end to the fundamental physical problems at hand?
- III. RQ3: Do AI-driven DSM models in precision agriculture truly stand up to the rigours of deployment? The question is whether they can handle processing latency, dynamic responsiveness and scalability while also respecting the biological limits of crops that are determinants of yield and quality in the marketplace.
- IV. RQ4: What methodological failings or other deficiencies have been put on record? One has to consider how such flaws stand in the way of a smooth transition from the confines of a trial to a working farm, all the more so in the case of rural agricultural economies with limited resources.

- V. RQ5: What does the literature project by way of novel approaches, algorithmic advances or a rethinking of the system to do away with model bottlenecks?

2.2 Definition of Research Queries

For the purpose of this study, we made use of IEEE Xplore, ScienceDirect, Web of Science, Google Scholar and Scopus as our principal digital sources. Structured query strings were put to them in order to turn up the publications of greatest relevance. A first pass was made with an assortment of keywords including “demand-side management”, “smart farming”, “precision agriculture”, “renewable energy”, “energy management”, “irrigation optimization”, “greenhouse climate control” as well as “AI”, “machine learning”, “IoT” and “agricultural electrification”.

2.3 Articles Inclusion and Exclusion Criteria

This method of retrieval yielded in excess of 100 publications. To narrow this to the final 85 studies, a rigorous screening process was applied. Inclusion criteria required papers to be peer-reviewed, published between 2020 and 2026, and directly focused on agricultural energy management. Papers were excluded if they focused solely on urban environments or lacked empirical or robust simulation data.

2.4 Results Synthesis and Analysis

In conclusion, the synthesized results were structured to systematically address each research question, yielding several key insights. A significant proportion of the studies focus on reducing energy consumption; however, there is a notable paucity of research regarding the dynamic, real-time adaptation of systems or the handling of biological loads from crops. Technologically, the literature frequently features methodologies such as LSTM networks, hybrid algorithms, gradient boosting and reinforcement learning; all are considered sound approaches to the problem of energy management in an agricultural setting.

3: SMART ENERGY MANAGEMENT SYSTEMS IN FARMING

3.1 Energy Management (EM)

EM involves the comprehensive process of planning, operating and monitoring the energy consumption and generation aim at optimizing the performance and also decreasing the cost of energy Asghar *et al.* (2023). The field of EM is a very broad one which consists of a number of processes or strategies which has been an area of interest for many. Mariano-Hernández *et al.* (2021) gave a review of EMS in buildings, showing the importance of DSM, predictive control, optimisation, fault detection and diagnosis. Energy efficiency can be enhanced in buildings by employing these strategies which will ensure the reliability of the system. Another area of focus is EM in microgrid operation. Energy Management is broadly classified into two major strategies that work together: Supply Side Management (SSM) and Demand Side Management (DSM).

3.1.1 Supply side management

SSM is refers to the set of methods, technologies and policies which are used by utility companies and grid operators in order to ensure that the generation of energy and its supply meets the energy demand. In the earlier days this was the primary strategy used to ensure that there is stability and it was focused on only large centralized energy generation systems like thermal and hydroelectric power plants (Cai *et al.*, 2022). While DSM is mainly focused on adjusting the time of use and the level of energy consumptions from the end user, SSM focuses on the producer and supplier’s side. The main objective is to ensure generation adequacy, maintain system reliability and to optimize the economic dispatch of the generating units (Cai *et al.*, 2022).

SSM has evolved from just a predictable exercise in fuel procurement to a more complex highly uncertain scheme caused by the need to decarbonize and also the integration of renewable energy sources (Aoun *et al.*, 2020). SSM problems are also divided into two; Unit Commitment (UC) and Economic Dispatch (ED). In UC the utility company or operator makes a decision on which generator

unit to turn ON or OFF during a specific period and ED involves deciding how much power each unit will supply to meet the demand most economically.

3.1.2 Demand side management

The concept of DSM emerged in the late 1970s. At that time, utility companies began looking for ways to influence how their customers used electricity (Abul Kalam *et al.*, 2024). Their primary goals were to reduce peak electricity demand and, as a result, postpone the need to build new power plants or infrastructure. By the 1990s, the understanding of DSM evolved to encompass a broader range of strategies. This refinement included approaches such as load shifting, which involves moving electricity consumption to off-peak hours, as well as electrification, promoting the use of electricity for processes previously powered by other energy sources, and fostering the strategic growth of power markets to better manage energy demand (Bogdanova *et al.*, 2023).

3.2 DSM Strategies and Demand Response Schemes

DSM programs are essentially a blend of two key strategies: enhancing energy efficiency and implementing active load management as seen in Figure 3.1. A widely accepted framework categorizes DSM into these two primary pillars: energy efficiency, which focuses on reducing overall energy consumption by upgrading or replacing less efficient equipment, and demand response, which involves strategically altering the timing of energy use (Nebey, 2024).

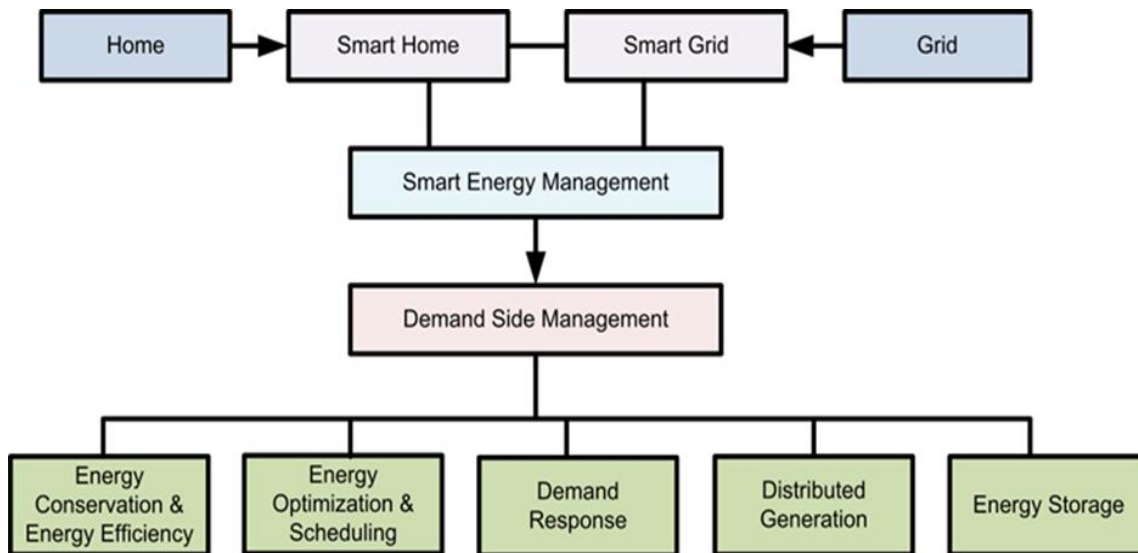


Figure 3.1: Energy management framework

Adapted from Iqbal *et al.* (2021)

Figure 3.2 visually represents the various functions of DSM techniques. Such functions involve managing electricity demand through peak shaving, increasing off-peak usage (valley filling), strategic energy conservation, load redistribution, and timing-based consumption shifts. Peak shaving and valley filling are direct methods of controlling electricity demand. Peak shaving aims to minimise energy usage throughout periods of highest demand, while valley filling seeks to increase consumption during periods of lowest demand. Strategic conservation, on the other hand, involves directly reducing overall energy demand on the consumer side. Both load shifting and time-shifting involve transitioning power consumption to off-peak intervals (Iqbal *et al.*, 2021).

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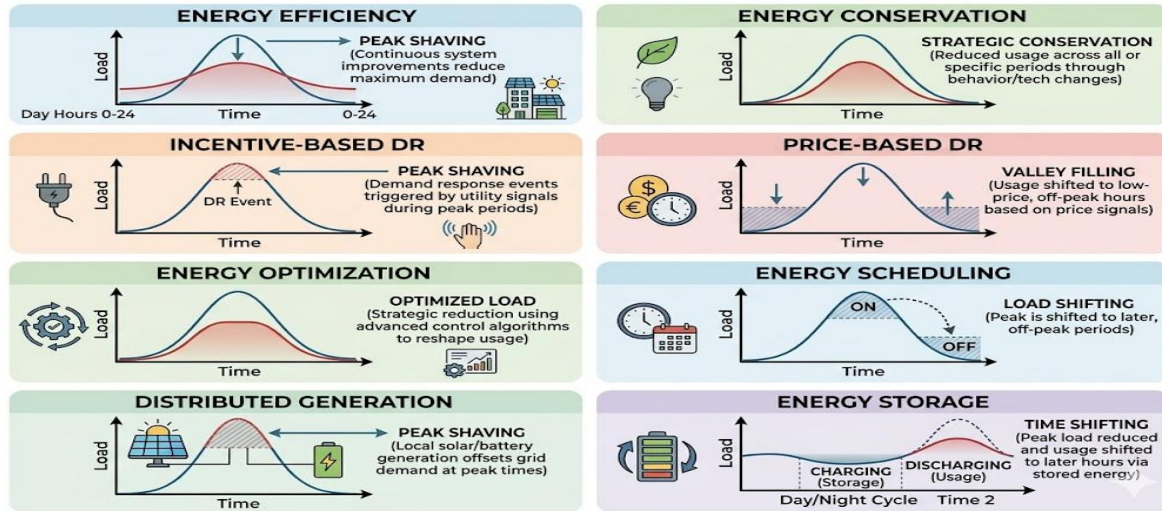


Figure 3.2: DSM Strategies

3.3 Theoretical Background of Smart Farming

A modern smart farm consists of many technical areas coming together including precision agriculture, cyber-physical systems, and sustainable energy engineering. Driven by the need to optimise the critical water-energy-food nexus, smart farming transitions agricultural operations from passive biological methods to highly mechanized, automated, and data-driven ecosystems (Azadi et al., 2021). To overcome grid unreliability and guarantee absolute biological safety, the modern smart farm's architecture has seen the integration of localized HRES with DSM schemes. As illustrated in Figure 3.3, this ecosystem relies heavily on the IoT to serve as a central nervous network. The architecture is structurally divided into three interconnected layers; the generation and storage layer which combines various energy generating and storage systems forming a resilient microgrid. This power is routed through a cyber-physical control layer, where an edge controller processes real-time data from a comprehensive sensor network monitoring various farming parameters such as soil moisture, temperature, and water levels. Finally, this intelligence governs the load layer, dynamically shifting or shedding deferrable agricultural loads based on environmental thresholds and battery state-of-charge without compromising overall crop health.

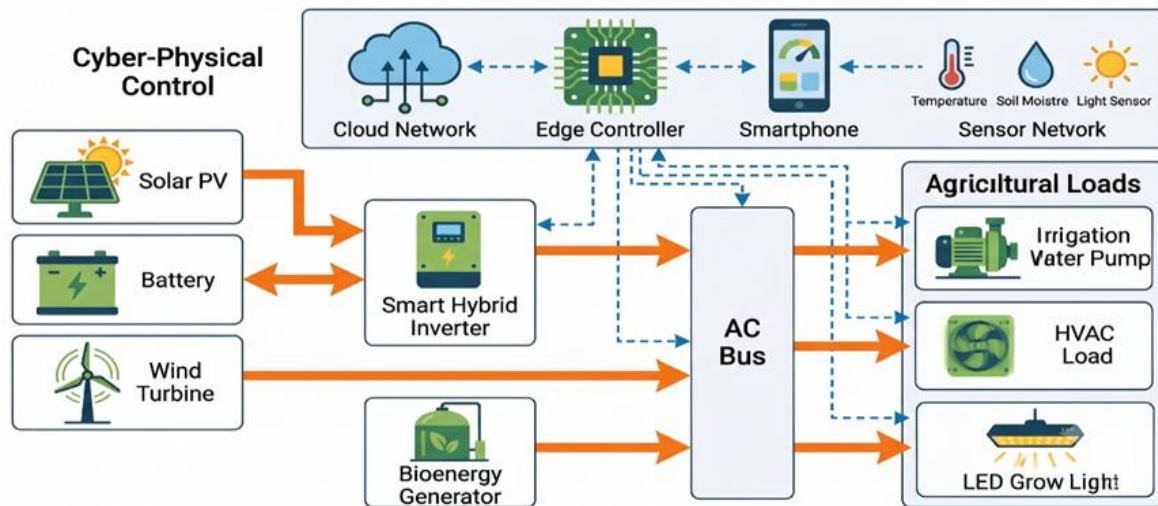


Figure 3.3: Architecture of a Modern Smart Farm

3.4 Energy Demands and Load Profiling in Smart Farms

Moving towards precision agriculture is one of the most important steps in ensuring global food production, which will alter the energy-water-food nexus (Iqbal et al., 2026). Advanced smart farms, which include both open-field precision and controlled indoor farming, greatly depend on automated

and data-driven systems in order to increase their yields and also optimise the use of resources (Nirosha et al., 2024).

3.4.1 Irrigation and water pumping systems

Irrigation systems are a very important but highly variable electrical load in both open field and greenhouse agriculture. Factors that influence the electrical power which is needed to move the water from its source to its needed destination are fluid dynamics, the elevation, and the friction of the pump system (Mansoor *et al.*, 2025). In irrigation, the main metric used in determining the required electrical power is Water Horsepower (WHP), which is a representation of the mechanical energy needed to move a certain volume of water against a total dynamic head (TDH) (Mushtaq et al., 2024). The mathematical representation is given in Equation 3.1:

$$WHP = \frac{GPM \times TDH}{3960} \quad (3.1)$$

where GPM represents the pumping rate in gallons per minute, TDH is the total dynamic head in feet, and the denominator 3960 serves as a universal conversion constant deriving from the weight of water and the definition of horsepower. Mechanical and electrical systems are prone to thermodynamic efficiency losses and this makes it very important to know the actual mechanical power that is needed at the shaft of the pump. This is called the Brake Horsepower (BHP) and it can be derived by considering the mechanical efficiency of the pump and the efficiency of the drive mechanism, given in Equation 3.2 where η_{pump} represents the mechanical efficiency of the pump, and η_{drive} represents the efficiency of the drive mechanism.

$$BHP = \frac{WHP}{\eta_{pump} \times \eta_{drive}} \quad (3.2)$$

By actively measuring these metrics, EMS controllers can engage in dynamic load profiling, prioritising energy dispatch precisely when mechanical efficiencies peak and water demands are critical.

3.4.2 Climate control and HVAC in controlled environments

Providing the optimal microclimate is one of the biggest consumers of energy in Controlled Environment Agriculture and greenhouses. About 30% of the energy used in these types of facilities is from powering heating, ventilation, and air conditioning (HVAC) systems which are used to regulate the internal environment against extreme weather variations (Çam *et al.*, 2025). Since temperature and humidity need to be continuously maintained, this creates a rigid base load that makes it very difficult to integrate renewable energy systems. In the Mediterranean, semi-arid, or tropical climate regions which are known for high solar irradiance, high heat is accumulated inside the greenhouse which requires constant operation of HVAC systems in order to prevent heat stress on the crops. This ventilation requirement can be expressed mathematically as seen in Equation 3.3.

$$Q_v = \frac{\tau \cdot R_{s,o-max} \cdot A}{\rho \cdot C_p \cdot \Delta T} \quad (3.3)$$

where Q_v is the required ventilation rate, τ is the greenhouse structural solar transmission coefficient, $R_{s,o-max}$ is the maximum outside solar radiation, A is the ground surface area, ρ is the density of the air, C_p is the specific heat capacity of air, and ΔT is the maximum permissible temperature difference between the indoor and outdoor environments.

3.5 IoT-enabled Farm Energy Monitoring and Smart Infrastructure

IoT is a wireless network that is incorporated with physical items like electronic devices, vehicles, structures, and other electronic devices (Konings *et al.*, 2022). It is a very important technology as it allows objects to obtain, analyze, process, control, and output the information remotely over the network by a computer-based system (Onike, 2025). It makes it possible for the user to control their system remotely over phone through the internet. As illustrated in Figure 3.4, which shows how

the interaction of multiple IoT devices is done as a cyber-physical system, it is a technology which has a wide range of applications in smart grids, smart buildings, and smart farms.

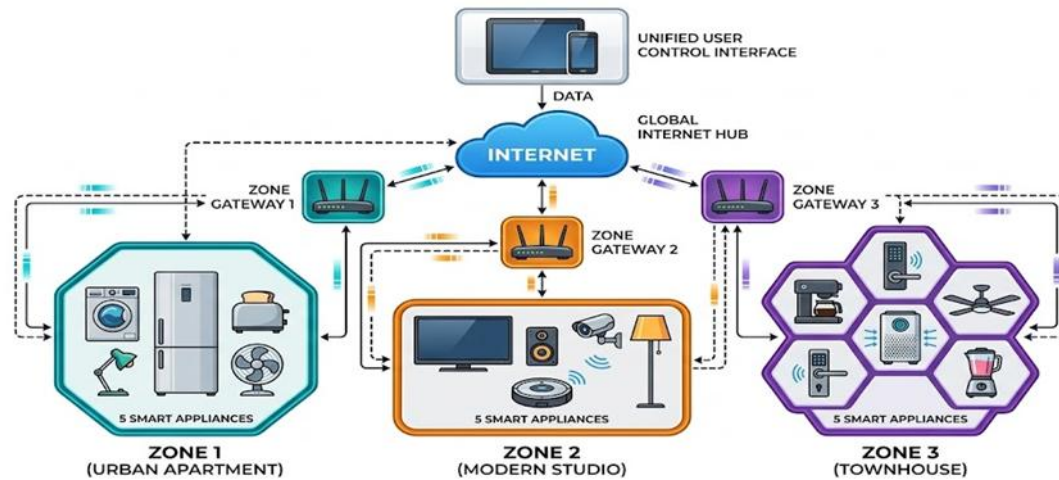


Figure 3.4: The Interaction Between IoT Devices

In modern agriculture, the way data is collected and processed is of paramount importance for ensuring operations are both accurate and as unencumbered as possible. There is scope for IoT to better monitor farm activities and pick up on any faults (Choudhary *et al.*, 2025). Research into agricultural energy has shown a marked interest in the use of IoT to manage irrigation; Al-Ali (2019) put forward an IoT solar system for smart irrigation by way of example. The design makes use of a single-board controller with its own Wi-Fi to link to the solar cells that furnish the power required. From the sensors in the field, it will take readings of soil moisture, temperature and humidity, then issue the actuation commands needed to run the irrigation pumps.

3.6 Renewable Energy Integration for Agricultural Operations

Adopting renewable energy is one of the key aspects for decarbonising agriculture to help tackle climate change, reduce dependency on fossil fuels and improve the economic viability of agricultural systems. Adetoro *et al.* (2023) performed techno-economic and environmental impact assessment of a hybrid renewable energy system with improved combined dispatching strategy for a north-central Nigeria dairy farm. Their best HRES design, made from 248 kW solar PV array, 2 kW wind turbine, 22 kW biogas generator and a diesel generator with nominal power of 92 kW + 658kWh battery storage gave LCOE \$0.148/kWh and NPC \$1.99 million. This LCOE is highly competitive when compared to Nigeria's current grid electricity tariffs and represents a significant cost reduction compared to the baseline of running diesel-only generators in off-grid rural areas. The Enhanced Combined Dispatch (ECD) strategy, which combines Load Following (LF) and Cycle Charging (CC) modes with six operation scenarios based on net load, battery state of charge (SOC), and energy balance forecasts was shown to perform considerably better than conventional dispatch methods. ECD provides significant reductions in CO₂ emissions (25% lower than CC, 14% lower than LF) as well as diesel consumption (from the base system of 84,351 L/year to only 3,110 L/year), demonstrating the environmental and economic advantages of optimized renewable integration.

The potential of biogas systems for agricultural energy applications has also received considerable attention due to the availability of organic waste streams on farms. Sanni *et al.* (2021) analysed the potential of off-grid solar PV/biogas power generation for a slaughterhouse in Ado-Ekiti, Nigeria, demonstrating that biogas from organic waste could provide reliable backup power to complement solar PV systems. The study utilised HOMER software for optimization and simulation, finding that incorporating biogas generation could reduce diesel consumption by 96% compared to diesel-only systems. The intermittent nature of solar and wind resources presents significant challenges for agricultural applications requiring continuous power supply. Studies by Rehman *et al.* (2024) addressed this challenge through the development of comprehensive frameworks integrating renewable energy resources with battery energy storage systems and precision robotics. Their work highlights the

importance of energy storage in enabling high renewable penetration in agricultural operations, noting that battery energy storage systems can increase the renewable fraction of agricultural microgrids from 20-40% up to 60-80% compared to standalone systems.

3.7 Energy Forecasting and Predictive Analytics

Accurate energy forecasting is critical for the management of an agricultural operation; it is what allows for the kind of proactive decisions that are needed in matters of demand response, storage and the dispatch of generation. In the studies at hand, the methodology is underpinned by an empirical approach to load profiling as opposed to the use of intricate digital twin simulations. The biological variables at play on a farm are too numerous for a conventional digital twin to put on the map with any precision, so a more robust way to do one's analytical forecasting is with targeted load profiling. Recent research has increasingly focused on hybrid machine learning architectures for this purpose in agriculture. In a 2025 study, Biswal *et al.* (2025) put forward a hybrid XGBoost-LSTM model to predict greenhouse energy demand; it makes use of Extreme Gradient Boosting to learn from static features and Long Short-Term Memory in order to recognise sequential patterns. With the addition of a priority-based DSM framework the model was able to cut average electricity costs by 17.3% and grid reliance by 7.1%, all with a MAPE of 5.3%. A comprehensive analysis of AI for power forecasting in renewable microgrids was conducted by Islam and Othman (2026). They compared the likes of ANN, Fuzzy Logic and ANFIS with deep learning of a more advanced nature such as Transformer, TCN or LSTM. Using hourly data in the field from the King Saud University microgrid in Riyadh, they identified the SE+LSTM as the optimal model, recording an RMSE of 0.7015 kW and a 2.01% MAPE. This was well above what could be obtained from the traditional models or even the TCN (RMSE 0.765 kW, 3.92% MAPE) and standalone LSTM (0.783 kW RMSE, 3.91% MAPE).

3.8 Smart Agro-Energy Policies and Farmer Engagement

For AI-driven energy management to be implemented in the agricultural sector, one needs more than technological advances; there is a requirement for sound policy and ways of engaging farmers. The policy landscape for agricultural energy management is characterized by significant regional variation. For instance, Nigeria's Electricity Act of 2023 eliminates the requirement for a licence to construct or run an electricity distribution or generation facility so long as capacity limits are observed. The Act is open to anyone wishing to do so, particularly where renewable sources are concerned. Gelchu *et al.* (2023) emphasised the importance of policy frameworks in enabling DSM in agricultural contexts. Their analysis of autonomous solar PV-based mini-grids for Ethiopian farms revealed that the cost-effectiveness of DSM strategies depends significantly on tariff structures and regulatory frameworks. Household loads showed the highest DSM impact (45.8% LCOE reduction), followed by productive use with night-time loads (20.7% LCOE reduction), suggesting that policy interventions targeting these load categories could yield substantial benefits. Farmer engagement and adoption of smart energy technologies is a critical factor in the success of AI-based energy management systems. Nigussie *et al.* (2020) highlighted the importance of incorporating indigenous farming and expert knowledge, regional weather information, and crop and soil-specific characteristics into IoT-based irrigation management systems.

3.9 Global Trends in AI-driven EMS in Agriculture

At its core, AI is the discipline of developing and studying intelligent systems or agents. For the purpose of making computers that are truly intelligent, one has been able to draw on techniques like soft computing, statistical learning and knowledge-based systems going back to the 1950s. An examination of 85 studies is visually represented in Figure 3.5, illustrating the annual publication trends in AI-based EMS over the 2020-2026 period. One can see from the data a consistent rise in research output, with the number of studies climbing from 10 in 2020 to 22 by 2025; this is indicative of the heightened interest, both in academia and in practice, for the use of AI in agricultural energy management. The trend also reflects rapid advancements in such technologies as IoT and deep learning that are putting new forecasting and optimisation at the disposal of EMS. As to how these are put to use in DR and what classifications they fall under, Figure 3.6 classifies the various AI approaches

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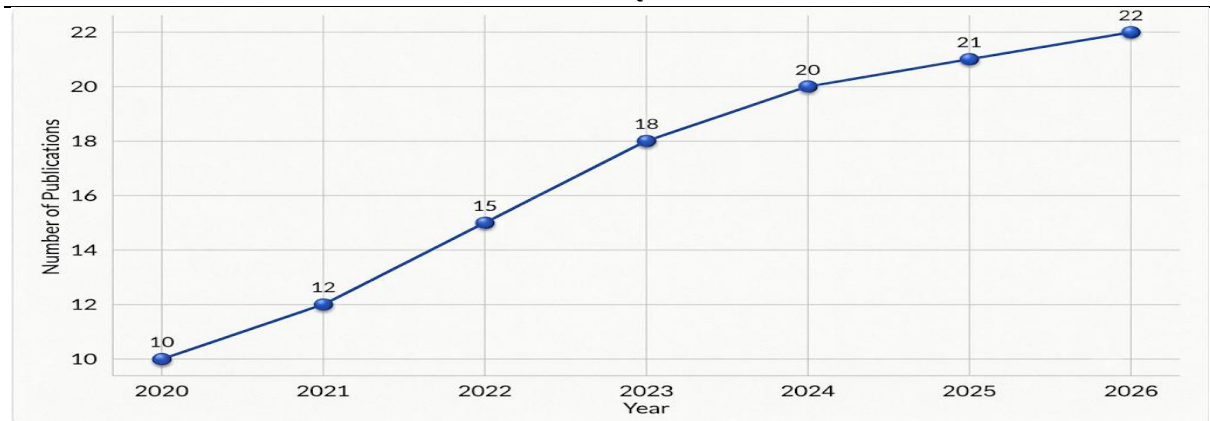


Figure 3.5: Rising research trend in AI-driven EMS for Agricultural Energy Management (Rehman *et al.*, 2025).

An analysis of global research into AI for agricultural energy management reveals notable patterns. In the last five years alone there has been a marked upturn in the number of papers produced in this area, which is testimony to an appreciation of what AI can do to solve the problems of agricultural energy. The bulk of the work on AI-driven agricultural EMS comes from a handful of places; China, Europe, the United States and India are the principal contributors by way of publications. However, developing regions are increasingly contributing to this research domain. Studies from these areas elucidate the particular opportunities and challenges to be had in resource-limited settings.

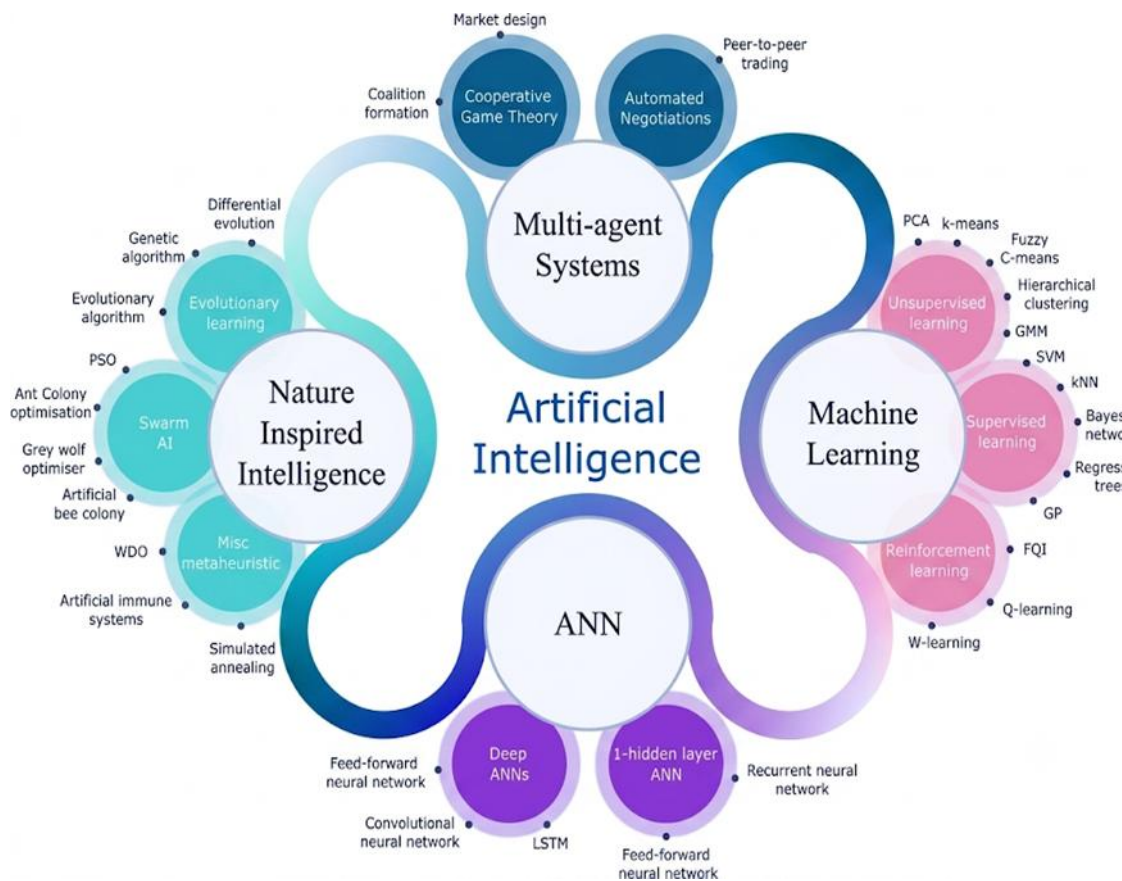


Figure 3.6: Classification of AI Techniques in Energy Management

Adapted from Antonopoulos *et al.* (2020)

4. OPTIMISATION TECHNIQUES FOR AI-BASED AGRICULTURAL ENERGY MANAGEMENT

4.1 Machine Learning for Agricultural Energy Optimisation

In the area of agricultural energy optimisation, ML has become integral to the field, providing the means to forecast, classify and optimise in a wide range of applications. One finds in its use supervised learning for prediction, unsupervised methods for clustering and pattern recognition, as well as reinforcement learning to handle adaptive control and make decisions. For the purposes of forecasting in agriculture, there is extensive recourse to supervised learning techniques such as ANNs, SVMs, random forests or XGBoost. Unsupervised learning has been applied to load profiling and the segmentation of customers within agricultural energy management. Priyanka *et al.* (2023) are one example; they made use of region-based clustering to see gains in energy efficiency from IoT agriculture networks and showed that with large scale deployments, the approach can do much to cut down on the communication overhead and energy used. Several studies have quantified the economic benefits to be had from ML-driven optimisation. In Sri Lanka, for instance, Witharama *et al.* (2024) found that 14.22% of electricity costs could be reduced through LightGBM forecasting given the present tariff system, and as much as 39.42% when market prices are time-varying.

4.2 Reinforcement Learning (RL) for Agricultural Demand Response

In the area of agricultural demand response, RL has demonstrated significant efficacy. It is the basis for adaptive energy management strategies which, through iterative learning, optimize how one makes operational decisions in a dynamic setting. RL algorithms are applied across various tasks in agricultural energy management: from the control of HVAC and irrigation scheduling to battery management. Q-learning, Proximal Policy Optimization (PPO), and Deep Q-Networks (DQN) are among the primary methods utilised. RL overcomes several limitations inherent in traditional rule-based methods when applied to this field. Abul Kalam *et al.* (2024) observe that an RL agent is able to adapt as conditions change and in so doing enhance its performance, learning the best control policies by way of engagement with the environment. The capacity of RL to optimize pricing strategies for service providers was shown by (Lu and Hong, 2019) in their work on an incentive-driven demand response framework for the smart grid, for which they made use of deep neural networks and reinforcement learning.

4.3 Swarm Intelligence for Renewable Energy Integration in Agriculture

The collective behaviour of social organisms is the source of inspiration for swarm intelligence (SI) algorithms, which have seen wide use in the integration of renewables on farms. With their capacity to tackle the kind of intricate optimisation issues that arise in agricultural energy systems, be it in the sizing, dispatch or scheduling of resources, SI algorithms are formidable instruments. Among them are Particle Swarm Optimization (PSO), Ant Colony and Artificial Bee Colonies (ACO, ABC) as well as the Grey Wolf Optimizer (GWO). A case in point is the work of Adetoro *et al.* (2023) who compared the performance of PSO, GA, and ABC in a Nigerian dairy farm to see how they would fare with HRES sizing. Ultimately, PSO demonstrated superior performance, delivering an LCOE of 0.162/kWh and an NPC of \$2.05m. The authors attributed this advantage to the way PSO can search the design space and home in on the optimum without sacrificing its balance of exploration and exploitation.

4.4 Hybrid and Ensemble Modeling Approaches for Agriculture

In the field of agricultural energy management, hybrid and ensemble models are demonstrating considerable efficacy. By drawing on the strengths of a number of AI techniques, such approaches have much to offer; they mitigate the limitations of individual methods through complementary capabilities and in most instances outperform a model on its own. One finds that the pairing of machine learning with evolutionary optimization is especially well suited to agricultural energy applications. A novel class of hybrid modeling is also gaining prominence in the form of physical models being brought together with data-driven ML. As an example of what can be done by marrying forecasting models to system simulation for a full appraisal of renewable energy performance, Punyam Rajendran and Gebremedhin (2024) made use of EnergyPLAN software in their multi-energy microgrid analysis,

putting deep learning-based solar power forecasts to work in the process. Also, recent frameworks have successfully merged Extreme Gradient Boosting (XGBoost) for analysing static environmental features with Long Short-Term Memory (LSTM) networks for sequential pattern recognition. Biswal *et al.* (2025) demonstrated that this hybrid approach is highly effective in greenhouse demand-side management, achieving a Mean Absolute Percentage Error of just 5.3% while reducing grid reliance.

5. LIMITATIONS IN AI-DRIVEN OPTIMIZATION FOR AGRICULTURAL ENERGY MANAGEMENT

5.1 Limited Scalability Across Diverse Farm Sizes

Current research is constrained by the limited scalability of AI optimization across the different sizes of farm. One will find in most of the literature a concentration on particular scales or types of farms, and little way to validate the findings over the whole range of agricultural operations, be it a smallholder or a large commercial concern. Priyanka *et al.* (2023) put forward a region-based network design as a means of scaling, one that can take in an assortment of nodes; yet they confined their validation to what was simulated, not to any real-world deployment.

5.2 The Quality and Availability of Data

For AI to be of use in managing agricultural energy, there are fundamental limitations imposed by the data. The models need to be trained and validated on datasets of sufficient size and quality, which are scarce in the agricultural sector, in developing nations especially. In rural SSA for instance, Nigussie *et al.* (2020) pointed out that with so few weather stations researchers must rely on satellite data for irrigation purposes instead of measurements from the ground.

5.3 Computational Demands of Off-grid Environments

Deploying AI in off-grid agricultural settings presents significant technical challenges given the complexity of the algorithms and the paucity of power, connectivity and computing resources to be found in remote areas. Such algorithms are energy and processing intensive. Biswal *et al.* (2025) have shown how these constraints can be met by running ML models that have been properly optimised on a Raspberry Pi 3B+ controller via edge computing.

5.4 Not Enough Adaptability When Conditions Change

Currently utilized approaches are limited in their ability to adapt to dynamic on-farm conditions. Energy management systems must adapt in real-time to dynamic equipment loads or abrupt meteorological changes, but AI models, being based on historical data, will not always react to something new.

5.5 Dealing with Older Farm Infrastructure

Furthermore, integrating AI energy management with legacy infrastructure poses substantial challenges. Much of what is already in place has not been built for the purpose of digital control or to gather data. Implementing monitoring and control systems can be a capital-intensive process and at times not possible from a technical standpoint. At Maizube Farm, Adetoro *et al.* (2023) had to install actuators and sensors in order to monitor and control the diesel pumps and other processing and irrigation equipment since they were not designed for it.

5.6 Lack of Focus on Farmer-centric and Ethical Considerations

Research into AI for agricultural energy management frequently overlooks ethical and farmer-centric considerations. The emphasis has been on the technical merits of the system, its accuracy and efficiency, rather than what bearing it has on the farmer's livelihood or autonomy in making decisions. Abul Kalam *et al.* (2024) observe that such matters as worker displacement, bias in the algorithm and data privacy have not been given the attention they warrant in the published work.

6. DISCUSSION, RESEARCH GAPS, AND SOLUTIONS

6.1 Research Gaps

Although the integration of intelligent technologies into agricultural systems has advanced rapidly, critical research gaps remain across the six primary thematic clusters identified in this review:

- I. **IoT-Enabled Farm Energy Monitoring:** Existing literature predominantly evaluates IoT telemetry and sensor topologies under controlled or simulated environments. A pronounced gap persists in long-term, empirical field validation under severe environmental conditions, intermittent rural connectivity, and sensor drift in open-field deployments.
- II. **Renewable Energy Integration in Agricultural Microgrids:** While techno-economic assessments of basic solar-diesel systems are common, research lacks comprehensive dispatch models capable of coordinating multi-source generation (solar PV, wind, and bioenergy) with battery storage against the highly non-linear, seasonal demand profiles of agro-industrial operations.
- III. **Predictive Energy Forecasting for Crop Storage and Processing:** Deep learning and hybrid architectures (such as XGBoost-LSTM) exhibit high predictive performance, yet their transferability is constrained by a severe scarcity of high-resolution, open-access agro-climatic datasets. Furthermore, current models rarely integrate biological growth stages directly into the load prediction loop.
- IV. **AI Optimisation of Farm Machinery and Operations:** Most algorithmic frameworks assume modern, digitally controllable loads. There is limited investigation into retrofitting legacy agricultural equipment with intelligent edge controllers or mitigating the physical wear and electromechanical constraints of retrofitted motors and pumps.
- V. **Smart Agro-Energy Policies and Farmer Adoption:** Energy management research frequently treats policy and regulatory mechanisms as static boundary conditions rather than dynamic variables. Few studies evaluate how decentralized energy policies (such as the Nigeria Electricity Act 2023) or localised tariff structures influence the financial viability of rural demand-side management.
- VI. **Blockchain and Peer-to-Peer (P2P) Energy Trading:** Decentralized energy trading among rural agricultural producers remains largely conceptual. There is a lack of field-tested, lightweight consensus algorithms capable of operating within the low-bandwidth, low-computational-capacity constraints typical of off-grid rural distribution networks.

6.2 Solutions

To address the identified research gaps and advance the practical deployment of intelligent agricultural energy systems, a transition from simulated environments to physical testbeds and demonstration sites is paramount. Developing modular, low-voltage hardware prototypes utilizing robust edge-level microcontrollers, such as ESP32 architectures, can enable real-time, multi-tiered load prioritization and fault detection. This approach allows agricultural energy management systems to function reliably without depending on continuous cloud or rural broadband connectivity, making it possible to integrate intelligent control seamlessly with legacy farm machinery.

Furthermore, to overcome the severe meteorological variability inherent in open-field environments, future forecasting models must prioritize hybrid machine learning architectures. Combining temporal sequence processing, like LSTM networks, with gradient boosting algorithms, such as XGBoost, can highly optimize weather-based energy forecasting and predictive dispatch logic for hybrid agricultural microgrids. This advancement must be coupled with the establishment of open-access agro-climatic datasets and standardized protocols for data sharing, which are essential to accelerate model training and allow researchers to systematically evaluate algorithmic performance across diverse climates.

Ultimately, the development of Agricultural Energy Demand Side Management (AGDSM) systems requires a participatory, interdisciplinary approach that actively involves agricultural practitioners, engineers, and policymakers. Researchers must proactively engage with regulatory frameworks to test the economic viability of these AI models under localized tariff structures and decentralized energy policies. In the context of Nigeria's development priorities, these findings

highlight a critical pathway for the nation's growth. Aligning with the conference theme to 'Harness Engineering to Drive Nigeria's Growth,' deploying AI-driven hybrid renewable systems in rural farming directly supports national food security and rural electrification mandates, effectively mitigating the impacts of unstable grid infrastructure.

7. CONCLUSION

In this systematic literature review we have evaluated the role that artificial intelligence plays in energy management systems as they are applied in agriculture. An analysis of 85 studies over the period 2020-2026 was carried out. Six distinct thematic clusters were identified in the review: from IoT farm energy monitoring and the use of renewables in agricultural operations, to forecasting energy needs for crop storage and processing; smart policy frameworks for agro-energy; and AI optimisation of heavy farming equipment. These serve to illuminate what is trending, where there are gaps and what lies ahead.

The analysis reveals the capacity of AI to transform how an on-farm operation consumes energy, be it through better integration of decentralised renewables in a microgrid or the demand-response strategies one can put in place for livestock and irrigation. The review's key findings are that hybrid ML methods will outperform standalone ones in terms of forecasting accuracy, and swarm intelligence, PSO in particular, is well suited to HRES optimisation. There are considerable energy savings to be had when AI and IoT are combined.

While the convergence of AI with technologies like 5G, blockchain and IoT offers new avenues for managing agricultural energy, the literature rarely details fully integrated platforms combining multiple technologies. It is a priority to develop AI techniques that take into account the seasonality and biological constraints of the sector, and to align energy management with wider sustainability concerns like soil health and water conservation. To make the most of the opportunities for innovation there will be a need for policy support and continued investment in research. In tackling the gaps, we have identified the community can help bring about agricultural energy systems of greater efficiency and resilience. This review provides a basis for researchers and energy policymakers, as well as agricultural engineers, to move forward with sustainable farm energy systems and deal with the implementation issues peculiar to the rural environment.

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