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AI-driven energy optimization and routing strategy for solar-powered wireless sensor networks in precision agriculture

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Abstract
Solar-powered wireless sensor networks are increasingly relevant for precision agriculture because they can support continuous observation of soil, crop, and microclimatic conditions without frequent battery replacement. Their practical use, however, is limited by uneven solar charging, spatially variable communication distance, packet loss, and the energy-hole effect around gateway nodes. This paper presents a revised artificial-intelligence-based framework for energy prediction, routing selection, and duty-cycle control in solar-powered agricultural sensor networks. The framework combines field sensing, energy-state monitoring, data cleaning, residual-energy forecasting, route scoring, and advisory-system integration. A routing score is proposed by jointly considering residual battery level, expected solar recharge, link quality, hop distance, forwarding load, and agronomic urgency of the sensed data. The model is designed for either gateway-level decision-making or lightweight distributed deployment, depending on farm size and sensor-node capacity. The proposed approach is evaluated conceptually through network-lifetime, packet-delivery, delay, dead-node, residual-energy, and data-continuity indicators. The discussion shows that energy-aware routing should not be treated only as a communication task; it also influences the availability of timely field information for irrigation scheduling, crop-stress detection, and farm resource management. Field validation across crop stages, seasons, and weather conditions is recommended before large-scale deployment.

Keywords: Artificial intelligence; solar-powered wireless sensor networks; precision agriculture; energy optimization; routing strategy; machine learning; farm monitoring

1. Introduction

Precision agriculture depends on the timely collection of field-level data. Soil moisture, soil temperature, relative humidity, canopy environment, light intensity, pest-risk indicators, and irrigation status can be recorded through distributed sensor nodes. These observations help farmers and advisory services decide when to irrigate, where to apply inputs, and how to respond to crop stress. Wireless sensor networks (WSNs) are suitable for this purpose because they can collect observations from multiple locations in the same farm rather than relying on one representative measurement (Akyildiz *et al.*, 2002; Vuran *et al.*, 2018) [2, 6].

Despite these advantages, WSN deployment in agricultural fields faces a persistent energy constraint. Small sensor nodes normally depend on limited batteries, and battery replacement across large, muddy, or remote fields can be costly and irregular. Communication consumes more power than simple sensing or short local processing, especially when nodes forward packets over long distances or serve as relays for other nodes (Anastasi *et al.*, 2009) [1]. As a result, some nodes may fail earlier than others and create gaps in the monitoring network.

Solar energy harvesting can extend network operation by allowing sensor nodes to recharge during daylight hours. In farms, however, solar availability is neither constant nor uniform. Cloud cover, seasonal changes, crop shading, dust on panels, and local placement of the node can change the charging rate. A routing protocol that repeatedly selects the same short path may overload nodes with weak battery status, while nodes with better solar recharge may remain underused. Therefore, routing decisions need to consider both current energy and expected future charging capacity.

Artificial intelligence can support this requirement by learning from previous energy, communication, and sensing patterns. Instead of selecting a route only through distance or hop count, an AI-based decision layer can consider residual battery energy, solar charging opportunity, link quality, data urgency, forwarding load, and field condition. For instance, a node reporting soil moisture below the irrigation threshold may be assigned higher transmission priority than a node reporting stable conditions. This makes routing more closely connected with farm decision-making rather than treating all data packets as equal.

The present paper develops a conceptual framework for AI-driven energy optimization and routing in solar-powered WSNs for precision agriculture. The emphasis is on a practical network-intelligence pipeline that can be tested later with real sensor-node data. The paper does not claim final field performance; rather, it outlines a structured method that can guide empirical deployment, algorithm design, and evaluation.

The objectives of the study are as follows

1. To develop an AI-based framework for reducing unnecessary energy consumption in solar-powered agricultural WSNs.
2. To explain how residual-energy prediction, solar charging status, link quality, and routing suitability can be modelled for sensor nodes.
3. To propose a stage-wise routing and duty-cycle process that combines sensing, preprocessing, prediction, path selection, and sleep-wake scheduling.
4. To connect routing reliability with irrigation scheduling, crop monitoring, and sustainable farm decision-making.
5. To identify implementation constraints and future directions for field validation.

2. Background and Literature Review

A wireless sensor network is a collection of small nodes that sense physical or environmental conditions and transmit the readings to a base station or gateway. In agriculture, the value of such networks lies in their ability to capture spatial variation. A single measurement cannot describe the whole field when soil texture, slope, irrigation distribution, canopy cover, and crop growth differ from one location to another. Distributed sensing improves the possibility of targeted management and reduces dependence on generalized field assumptions.

Energy conservation has been a central research issue in WSNs. Nodes spend power on sensing, computation, storage, radio listening, transmission, and packet forwarding. Radio communication is usually one of the major sources of energy drain, particularly when traffic must travel through relay nodes (Anastasi *et al.*, 2009) [1]. Protocols such as LEACH and PEGASIS were developed to reduce unnecessary communication and balance energy consumption through clustering or chain-based transmission (Heinzelman *et al.*, 2000; Lindsey and Raghavendra, 2002) [3, 4].

Agricultural WSNs introduce additional complexity because environmental conditions change continuously. The soil-water condition, crop stage, canopy density, weather, and irrigation schedule affect both the value of the collected data and the operating condition of the node. Jawad *et al.* (2017) [8] reviewed energy-efficient WSNs in precision agriculture and emphasized that routing and energy management remain practical barriers for long-term field monitoring.

Solar energy harvesting addresses part of the energy problem by adding a renewable energy source to the node. Energy harvesting systems can reduce dependence on manual battery replacement, but they require control mechanisms that match the energy demand of the node with the energy being harvested (Kansal *et al.*, 2007) [5]. A node that receives strong sunlight during the day can forward more traffic, whereas a node under crop shade or cloud conditions should be protected from excessive relay tasks.

Machine learning provides tools for forecasting energy availability and communication reliability. Regression models, decision trees, random forests, gradient boosting, support vector regression, neural networks, and reinforcement-learning methods can be used to estimate residual energy, link stability, traffic burden, and node-failure risk. Deep learning may be useful when large historical datasets are available, while smaller models are more appropriate for low-power edge devices. The choice of model should therefore depend on the memory, processor, and energy profile of the field node.

In precision agriculture, the importance of a packet also matters. Soil moisture during flowering, irrigation leakage, frost risk, pest warning, or heat-stress information may require faster delivery than routine readings from stable areas. An adaptive routing system should therefore combine network variables with agronomic priority. This integration is the main distinction between a general energy-aware WSN protocol and a precision-agriculture routing strategy.

3. Proposed Methodology

The proposed methodology follows a sequential network-intelligence pipeline. First, sensor nodes collect agricultural readings and energy-state information. Second, the gateway or local node cleans and normalizes the data. Third, a prediction model estimates residual energy and routing suitability. Fourth, a route-selection module chooses the next hop according to energy, solar status, link condition, and data priority. Fifth, the duty-cycle controller modifies sensing and transmission frequency. Finally, reliable observations are passed to a farm advisory layer for irrigation or crop-management decisions.

The network contains solar-powered nodes distributed across the field. Each node may contain sensors for soil moisture, soil temperature, air humidity, light intensity, or other crop-environment variables. The same node also records battery voltage, solar-panel output, packet-transmission status, signal strength of neighbouring nodes, hop distance, and forwarding burden. These variables become the feature set for the AI model.

Two deployment arrangements are possible. In a centralized arrangement, the gateway receives node-state information and calculates routing decisions for the whole network. This option is easier to manage and is suitable for small to medium farms. In a distributed arrangement, each node runs a compressed model and makes local routing decisions using its own status and limited neighbour information. This option is more resilient but requires careful model compression, communication control, and energy-aware computation.

3.1 Data Acquisition and Preprocessing

Raw agricultural and energy data may contain missing values, repeated readings, abnormal jumps, sensor drift, or communication errors. Battery and solar-panel readings also change throughout the day, and a single extreme value can distort routing decisions. Therefore, preprocessing is required before prediction or routing selection.

The preprocessing stage includes timestamp alignment, removal of impossible values, filtering of noisy sensor readings, normalization of battery and solar variables, and classification of data priority. For example, soil moisture below an agronomic threshold may be labelled as urgent, while values within the normal range may be assigned routine priority. Similarly, a node with high battery level, stable solar input, and strong link quality may be treated as a preferred forwarder, while a weak node may be protected from heavy relay traffic.

3.2 AI-Based Energy Prediction

The energy-prediction module estimates whether a sensor node can continue sensing and forwarding data during the next monitoring interval. Input variables include present battery level, recent solar charging rate, expected daylight period, historical energy use, number of packets forwarded, communication distance, signal strength, and previous failure records. The output may be expressed as predicted residual energy for the next hour, day, or irrigation cycle.

Different modelling choices are possible. Random forest and gradient boosting are suitable when the relationship between variables is nonlinear but tabular. Support vector regression may be useful for smaller datasets. Long short-term memory networks can model time-dependent harvesting and consumption patterns, but they may be too heavy for small nodes unless computation is shifted to the gateway. Lightweight neural networks or compressed tree models may be more practical for field-level deployment.

3.3 Routing Strategy and Duty-Cycle Control

A conventional routing protocol may select the nearest or shortest available route, but repeated selection of the same path can drain relay nodes and create network partitions. The revised AI-driven strategy assigns a routing score to each candidate next-hop node. The score combines normalized residual energy, predicted solar recharge, link quality, hop distance, traffic load, and crop-data priority. A simplified score can be expressed as:

$$\text{Routing Score} = w_1(\text{Eres}) + w_2(\text{Esolar}) + w_3(\text{LQ}) + w_4(\text{Pdata}) - w_5(\text{Distance}) - w_6(\text{Load})$$

In this expression, Eres represents current residual energy, Esolar represents expected solar recharge, LQ represents link quality, Pdata represents agronomic data priority, Distance represents hop or communication cost, and Load represents the current forwarding burden of the candidate node. The weights can be selected empirically according to farm size, data urgency, and hardware capacity.

Duty-cycle control further improves energy efficiency. Nodes do not need to remain active at all times when the field condition is stable. A node can increase its sleep interval and reduce transmission frequency during normal conditions, while it can temporarily increase sensing frequency during irrigation, heat stress, pest-risk periods, or abnormal moisture decline. The same AI layer can therefore recommend both the route and the sleep-wake schedule.

4. Proposed System Architecture

The proposed architecture contains six linked modules: sensor-data input, preprocessing, AI-based energy prediction, routing selection, duty-cycle control, and precision-agriculture advisory integration. The sensor-data input module captures both agronomic variables and node-health variables. The preprocessing module creates a consistent feature set. The prediction module estimates energy availability and route suitability. The routing module selects the next hop. The duty-cycle controller adjusts sensing and transmission behaviour. The advisory module receives reliable field observations for irrigation scheduling, crop-stress monitoring, and farm management.

Table 1: Proposed system workflow for AI-driven solar-aware WSN routing

Stage	Input	AI/technical method	Expected output
Field sensing	Soil, weather, and crop sensor readings	Sensor-node acquisition	Raw agricultural observations
Energy monitoring	Battery level, solar voltage, solar current	Energy-state recording	Node energy profile
Preprocessing	Raw sensor and energy data	Filtering, normalization, and timestamp alignment	Clean feature set
Energy prediction	Historical and current node information	ML regression or time-series prediction	Expected residual energy
Routing decision	Energy, link quality, forwarding load, and data priority	AI-based routing score	Best next-hop node
Duty-cycle control	Predicted energy and farm urgency	Adaptive sleep-wake scheduling	Reduced power consumption
Advisory integration	Reliable field data	Decision-support rules	Precision-farming recommendation

5. Illustrative Results and Performance Evaluation

The results in this paper are illustrative and are intended to show how an empirical study may evaluate the proposed framework. In a real deployment, sensor data should be collected across several crop stages, weather patterns, and solar-charging conditions. Evaluation should include both network performance and agricultural usefulness because energy saving alone is not sufficient if urgent farm data are delayed or lost.

Network performance may be measured through network lifetime, packet-delivery ratio, end-to-end delay, residual energy, number of dead nodes, and routing overhead. Agricultural usefulness may be measured through continuity of soil-moisture data, correctness of irrigation alerts, delivery of stress warnings, and reduction in missing field observations.

6. Discussion: The proposed framework shows that energy optimization in agricultural WSNs is not only a technical communication issue. When sensor nodes fail early, the farm loses visibility of soil and crop conditions. This can affect irrigation timing, input management, crop-stress detection, and the reliability of advisory decisions. A routing strategy that protects weak nodes and uses stronger solar-charged nodes can reduce these risks.

A major advantage of the approach is adaptability. Farm conditions vary by time of day, weather, season, and crop stage. Solar charging improves during bright conditions and weakens during cloudy or shaded periods. Soil moisture may remain stable for several days and then become critical during dry weather or high crop-water demand. Fixed routing and fixed sensing schedules cannot respond adequately to such changes. AI-based routing can update decisions as the condition of the node and the value of the data change.

Table 2: Suggested performance indicators for field validation

Component	Metric	Purpose	Interpretation
Energy optimization	Residual energy	Measures remaining node power	Higher value indicates longer operation
Routing	Packet-delivery ratio	Measures successful data transmission	Higher value indicates reliable communication
Routing	End-to-end delay	Measures time taken to reach the gateway	Lower delay is better for urgent alerts
Network health	Number of dead nodes	Measures node failure	Lower number shows improved network lifetime
AI model	Prediction error	Measures accuracy of energy forecast	Lower error supports better route selection
Agricultural output	Data continuity	Measures missing field readings	Higher continuity supports decision-making

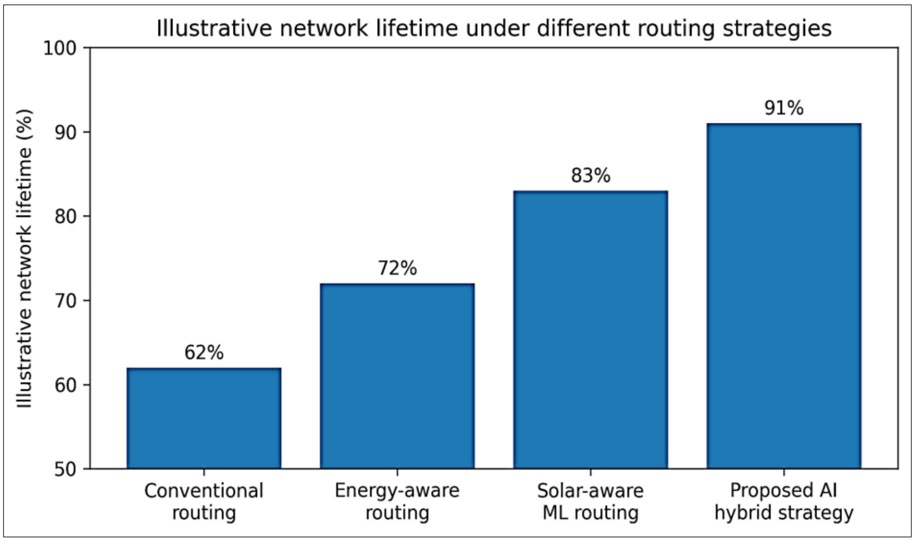

Fig 1: Illustrative network-lifetime improvement under different routing strategies.

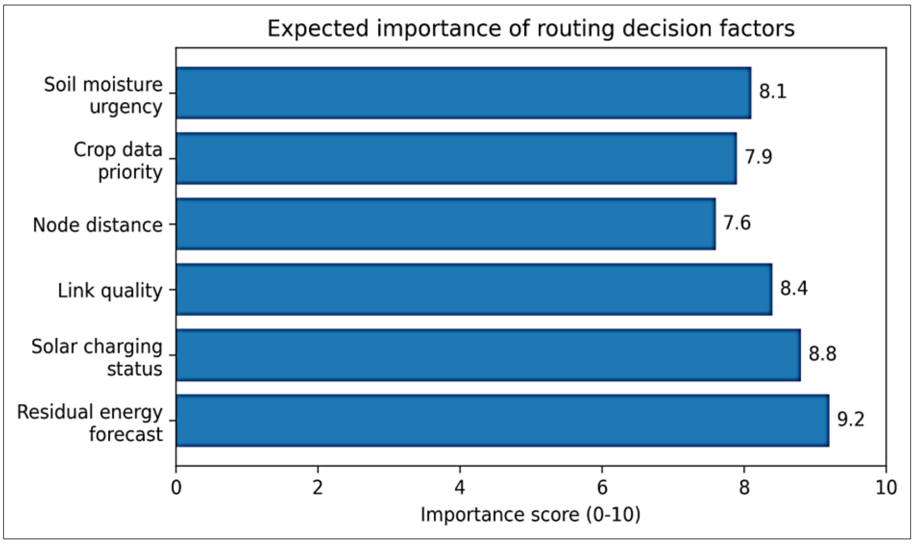

Fig 2: Expected importance of routing decision factors in AI-driven energy optimization

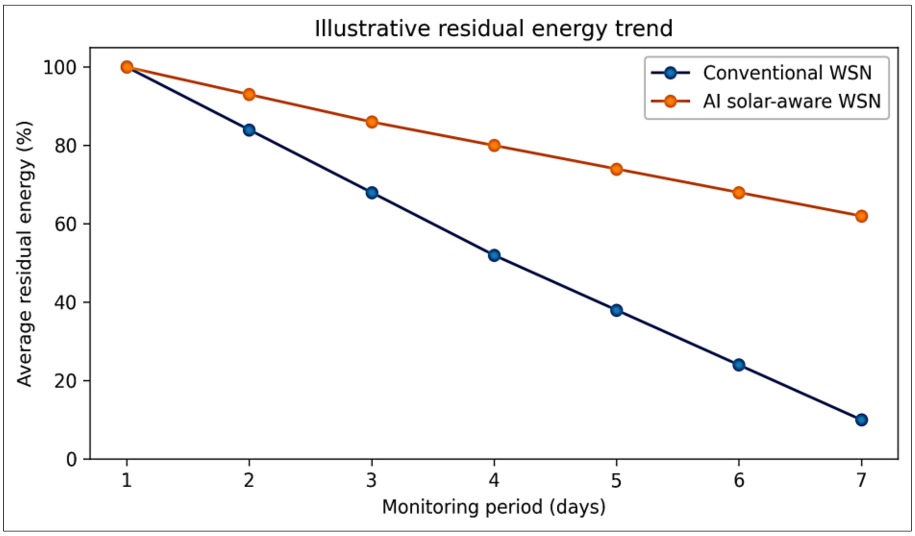

Fig 3: Illustrative residual-energy trend comparing conventional and AI solar-aware WSN operation.

The framework also supports sustainability. Longer network life reduces maintenance visits, battery replacement, and electronic waste. More reliable soil-moisture and stress data can help avoid unnecessary irrigation and may improve the timing of crop-protection and nutrient-management decisions. In this sense, the proposed system links network intelligence with the environmental goals of precision agriculture.

At the same time, implementation must be realistic. A complex AI model running directly on a small sensor node may consume more energy than it saves. Practical deployment may require gateway-based computation, compressed models, hybrid cloud-edge processing, or rule-assisted machine learning. Explainability is also important. Engineers, farm managers, and researchers should be able to understand why a node was selected as a relay or why another node was placed in sleep mode.

7. Limitations and Future Scope

The main limitation of this paper is that it presents a conceptual and illustrative framework rather than a completed field experiment. The values shown in the figures should be treated as demonstration values until replaced by real measurements from solar-powered sensor nodes. Before journal submission or technical adoption, the framework should be validated using multi-season field data across different crops, weather conditions, and node placements.

Future work should compare the proposed AI-driven strategy with conventional routing, energy-aware routing, solar-aware routing, and reinforcement-learning-based routing under the same farm layout and node density. Such comparison should use identical initial battery capacity, solar-panel size, communication range, packet interval, and gateway location. Without controlled comparison, improvement in network lifetime or data continuity may be difficult to attribute to the routing method itself.

Additional practical factors also need examination. These include solar-panel orientation, battery ageing, sensor calibration, dust accumulation on panels, gateway maintenance, communication interference, hardware cost, and repair requirements. A low-cost system is more likely to be adopted by farmers than a technically sophisticated but expensive architecture.

A useful future direction is integration with crop models and advisory systems. If the system knows the crop stage, it can assign higher priority to moisture data during flowering or fruit filling, temperature data during heat-sensitive stages, and disease-risk data during humid periods. Combining agronomic intelligence with network intelligence may make WSNs more useful for farmers.

Cybersecurity and data privacy should also be included in future designs. Farm-sensor data may reveal irrigation schedules, crop condition, and production trends. Secure communication, authenticated access, and responsible storage should therefore be part of the final deployment architecture.

8. Conclusion

This paper presented a revised AI-driven framework for energy optimization and routing in solar-powered wireless sensor networks for precision agriculture. The framework combines field sensing, preprocessing, energy prediction, routing-score calculation, adaptive duty-cycle control, and advisory-system integration. It considers residual energy, solar recharge, link quality, forwarding load, communication distance, and agronomic data priority when selecting a route. The conceptual analysis indicates that AI-based routing can improve network lifetime, reduce node failure, support reliable data delivery, and strengthen the usefulness of field observations for irrigation and crop management. However, the method should be validated with real field data before it is considered deployment-ready. Multi-season trials, lightweight model design, comparison with existing routing protocols, and integration with farm advisory systems are recommended as the next research steps.

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Appendix A. Suggested Dataset Structure for Field Validation

Variable group	Example variables	Purpose
Node energy	Battery voltage, current, residual energy, solar-panel output	Energy prediction and duty-cycle control
Network quality	RSSI, packet loss, delay, hop count, neighbour count	Route selection and reliability analysis
Agricultural sensing	Soil moisture, temperature, humidity, light intensity	Precision-agriculture monitoring
Temporal context	Time of day, season, weather condition, crop stage	Solar and crop-context interpretation
Decision output	Selected route, sleep interval, alert priority	Evaluation of routing strategy