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Smart Irrigation Enhancement Through UAV-Based Clustering and Wireless Charging in Wireless Sensor Networks

Emad S. Hassan [1,*], Abdoh Jabbari [1] and Ayman A. Alharbi [2]

[1] Department of Electrical and Electronics Engineering, College of Engineering and Computer Science, Jazan University, Jizan 45142, Saudi Arabia; ajabbari@jazanu.edu.sa
[2] Computer and Network Engineering Department, College of Computing, Umm Al-Qura University, Makkah 24382, Saudi Arabia; aarharbi@uqu.edu.sa
* Correspondence: eshassan@jazanu.edu.sa

Abstract: Wireless sensor networks (WSNs) enable large-scale data collection across wide areas but face significant challenges, including limited energy resources, unbalanced energy consumption, and inefficient data transmission, leading to reduced network lifetime and poor reliability. To address these issues, this paper proposes an energy-efficient clustering scheme that integrates unmanned aerial vehicle (UAV)-assisted data collection and wireless power transfer (WPT) to enhance WSN performance in smart irrigation applications. The proposed scheme divides the network into two regions: a central circular area containing standard nodes and an outer region divided into four clusters housing advanced nodes. It dynamically adjusts cluster formation, optimizes cluster head (CH) selection based on residual energy, minimizes transmission hops, and ensures the shortest possible UAV path, thereby reducing energy consumption. Additionally, UAV-based WPT provides continuous energy replenishment, mitigating the hotspot problem and extending network lifetime. Extensive simulations demonstrate that the proposed scheme reduces energy consumption by up to 13.16%, enhances data collection efficiency by 8.84%, and extends network lifetime by more than 9.6% compared to Yoon's scheme. Additionally, the proposed scheme achieves 26% higher residual energy and a 43% increase in throughput over Yoon's scheme. Moreover, in smart irrigation applications, the proposed scheme reduces water consumption by approximately 20%, demonstrating its effectiveness for sustainable precision agriculture.

Keywords: WSNs; UAV; WPT; hotspot problem; smart irrigation; water consumption

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Academic Editors: Fei Liu and Pablo Rodríguez-Gonzálvez

Received: 10 February 2025
Revised: 6 March 2025
Accepted: 21 March 2025
Published: 26 March 2025

Citation: Hassan, E.S.; Jabbari, A.; Alharbi, A.A. Smart Irrigation Enhancement Through UAV-Based Clustering and Wireless Charging in Wireless Sensor Networks. *Drones* **2025**, *9*, 253. https://doi.org/10.3390/drones9040253

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1. Introduction

The scarcity of water is one of the most important challenges facing the world. Therefore, water consumption and irrigation management have received significant attention. Conventional irrigation consumes large amounts of water through dissipation and drainage. Therefore, it is considered to be one of the highest forms of water consumption in the world. Moreover, conventional irrigation methods sometimes have negative effects on the quality of agricultural crops due to over- or under-irrigation. Therefore, it has become necessary to propose smart irrigation techniques aimed at reducing water consumption without affecting the quality of agricultural crops. Using recent technologies such as wireless sensor networks (WSNs) and the internet-of-things (IoTs) can achieve this aim [1–6].

WSNs consist of many distributed low-cost sensors which monitor and collect data from the surrounding field and forward it to a gateway for further processing. These sensors are typically distributed across a geographical area, and they can monitor a diverse range of environmental parameters, making them a fundamental element of the IoTs

ecosystem [2]. They find application in various sectors, including but not limited to; agriculture, environmental monitoring, healthcare, traffic management, and security and safety [2–9]. In last few years, WSNs have been applied to the agricultural sector to overcome the limitations of conventional irrigation. Using WSNs in the agricultural sector can achieve several benefits, such as reducing water consumption, achieving better crop quality and quantity, conserving energy and reducing costs, and saving farmers time and effort. To obtain these benefits, we design and implement a smart irrigation technique that utilizes WSNs to monitor important environmental parameters, such as humidity, temperature, and soil moisture, which results in superior smart and automatic cultivation.

Smart irrigation systems represent a technological leap forward in the domain of agriculture, offering an intelligent and data-driven approach to water management [7–9]. These systems integrate advanced technologies, such as WSNs and the IoTs, to monitor and analyze key environmental parameters like soil moisture, temperature, and weather conditions. By utilizing real-time data, smart irrigation systems enable precise and automated control over the water supply to crops, ensuring that they receive the optimal amount of water needed for growth. The implementation of such systems not only enhances water efficiency but also contributes to resource conservation, as water is applied judiciously based on actual crop requirements. Moreover, smart irrigation systems often incorporate connectivity features, allowing farmers to remotely monitor and control the irrigation process through mobile applications or centralized platforms. This not only streamlines agricultural operations but also empowers farmers with timely insights for better decision-making.

Despite the remarkable progress in WSN research and its applications, several challenges persist [10,11]. Key issues include energy consumption, scalability, security, network lifetime, and limited communication range. These problems hinder the widespread adoption and reliability of WSNs in various domains. One of the most critical challenges in WSNs is the limited energy availability of sensor nodes, which significantly impacts network performance and longevity [12,13]. Since most sensor nodes rely on battery power, frequent battery replacements or recharging are impractical, especially in large-scale or remote deployments. Energy harvesting techniques, such as solar power, offer a potential solution [14], but their efficiency depends on environmental conditions, making them unreliable for continuous operation. Existing energy management strategies, such as duty cycling and data aggregation, help optimize power consumption but do not fully address the issue of energy depletion in high-traffic areas. As a result, energy-efficient protocols and advanced power transfer methods are necessary to enhance the sustainability of WSN-based applications, including smart irrigation systems.

Another major issue in WSNs is the hotspot problem, which arises due to the uneven energy consumption among sensor nodes [15–18]. In multi-hop communication networks, nodes closer to the base station (BS) are burdened with relaying data from distant nodes, leading to accelerated energy depletion. This creates energy imbalances, where certain nodes die prematurely, resulting in network fragmentation and reduced data transmission reliability. Traditional clustering and routing protocols often fail to mitigate this issue effectively as they do not dynamically adapt to energy levels across the network. Therefore, innovative clustering techniques, adaptive data collection mechanisms, and wireless power transfer (WPT) solutions are required to address the hotspot problem and ensure a prolonged and stable network operation.

This paper introduces a new clustering scheme designed to partition the designated area into two distinct regions. The initial region is situated at the network's center and is delineated by a circular area, housing a category of nodes referred to as standard nodes. The secondary region encompasses both sides of the circle and is further subdivided into

four clusters, two on each side, comprising advanced nodes. In this proposed scheme, unmanned aerial vehicles (UAVs) function as mobile sinks, traversing the network to collect data from optimized clusters. Simultaneously, WPT is employed to wirelessly charge both fixed sink and helper nodes, with adaptive data collection rates based on available energy levels. This innovative approach mitigates the hotspot issue, leading to enhanced overall network connectivity and performance.

2. Related Work

A thorough examination of the existing work underscores the wealth of research and innovations surrounding WSNs. Researchers have delved into various facets of WSNs, encompassing critical aspects such as energy consumption, scalability, security, and network lifetime. The body of literature reflects the relentless pursuit of solutions to these challenges, with a focus on enhancing the overall performance of WSNs [10,11]. A significant portion of the research has been dedicated to tackling the issue of energy consumption in WSNs. Scholars have explored novel techniques and algorithms aimed at minimizing energy expenditure while ensuring efficient data collection and transmission. These efforts strive to extend the operational lifetime of sensor nodes, a key factor in the sustainability of WSNs.

The study in [15] delves into the critical issue of limited power resources influencing the likelihood of sensor network malfunctions. The research focuses on calculating the energy consumption of sensor nodes and estimating the service life of their power supply elements. The study compares energy consumption between conventional methods and neural network-based approaches, revealing that while neural networks can enhance processing efficiency, they also introduce additional power overheads. However, the research does not address potential strategies for optimizing neural network energy consumption or integrating energy-harvesting techniques to extend network lifetime, leaving room for further exploration into energy-efficient WSN deployments.

Recent research has explored UAV-enabled mobile crowdsensing (UMCS) as a promising approach for large-scale data collection [16]. However, relying solely on UAVs with limited energy poses significant challenges for covering an entire city efficiently. A hybrid optimization framework for age-of-information (AoI) minimization has been proposed, integrating distributed workers as the primary data collectors while utilizing UAVs to gather data from sensor nodes (SNs) that lack worker connectivity. While this approach improves data collection coverage, it has some limitations. The framework depends heavily on the availability and reliability of distributed workers, which may not always be consistent, leading to potential data gaps. Furthermore, its computational complexity may pose scalability challenges in large-scale networks with dynamic environments.

In the realm of wireless sensor networks, the conventional model grapples with inherent limitations stemming from finite battery energy, posing a substantial constraint on network lifetime. Addressing the problem of the finite battery energy of WSNs, the authors in [17] explore the viability of a sensor network operating on wireless energy transfer. The study envisions a scenario where a mobile charging vehicle periodically traverses the sensor network, wirelessly replenishing the energy of sensor nodes. While the proposed scheme in [17] is helpful, it is also variable and insufficient to meet high energy demands.

Scalability is another pivotal area of investigation in WSNs. As the demand for larger and more complex networks grows, researchers have sought to develop scalable solutions that can accommodate the expansion of WSNs without compromising performance. Scalability improvements involve innovative clustering algorithms and network topology control techniques. To address the challenges posed by the uneven distribution of nodes and limited energy resources in WSNs, the work in [18] introduces a clustering routing

algorithm based on hierarchical clustering. Notably, the algorithm eliminates the need for pre-calculating the optimal number of cluster heads. Initially, the randomly distributed nodes in the network are organized into several primary clusters using the hierarchical clustering algorithm. During network operation, cluster selection is based on both the node's residual energy and its position within the original clusters. However, this approach does not account for dynamic energy variations over time, which may lead to inefficient cluster head selection in rapidly changing network conditions.

The work in [19] introduces an energy-efficient routing protocol known as multi-threshold segmentation-based energy-efficient routing protocol (EERPMS) to enhance the rationality of cluster formation and cluster head (CH) selection. Although EERPMS improves CH selection, it does not incorporate adaptive mechanisms to dynamically adjust thresholds based on real-time network conditions, which could lead to suboptimal energy utilization. While the authors in [20] address the critical concern of energy conservation in WSNs by introducing the energy-saving fuzzy clustering routing algorithm (EFCR), EFCR still relies on predefined fuzzy rules, which may not be flexible enough to adapt to unpredictable network dynamics, thereby limiting its effectiveness in highly dynamic environments. Many of the existing clustering algorithms suffer from the drawback of employing fixed CH election methods in each clustering round, resulting in the continuous selection of unsuitable nodes as cluster heads. This, in turn, accelerates node energy depletion and leads to a shortened network lifespan.

Prolonging the network lifetime of WSNs has been a focal point in the literature. Researchers have explored methods to maximize the lifespan of sensor nodes, including optimized energy harvesting techniques, duty cycling, and node replacement strategies. Extending network lifetime is essential for reducing maintenance costs and ensuring the longevity of WSN deployments. The work in [21] addresses charging behavior by introducing a charging scheduling scheme known as partial charge. The scheme strategically enables the partial charging of sensor nodes, minimizing overall node downtime and consequently extending the network's lifespan. However, the partial charge approach assumes a predictable energy demand pattern, which may not be applicable in scenarios where energy consumption varies unpredictably.

While in [22], the authors explore the residual-energy awareness feature of sensor nodes in time-varying WSNs, presenting an analysis and modeling approach using a Markov chain. The Markov chain allows for the evaluation of state-transition probabilities (STP) concerning the energy levels of nodes with undetermined and deterministic residual energy. Despite its effectiveness in energy-aware modeling, the approach does not incorporate real-time feedback mechanisms to adjust network operations dynamically based on energy state changes. To reduce computational overhead, a spatial discretization scheme is introduced for constructing a charging route for the mobile charger. Subsequently, a path optimization scheme is devised to enhance charging utility [23]. However, the optimization scheme primarily focuses on charging efficiency and does not fully account for mobility constraints, which could affect the practicality of the approach in real-world deployments.

Recent research has explored the integration of mobile ad hoc networks (MANETs) and IoTs-based WSNs to enhance connectivity and energy efficiency in heterogeneous networks. The MANET-based energy saving optimization (MANET-ESO) technique has been proposed in [24], which establishes trusted routes between sensors and gateway nodes, improving network reliability while reducing energy consumption. While MANET-ESO focuses on energy-efficient routing in heterogeneous networks, it does not incorporate UAV-assisted data collection or WPT, which are key features of the proposed scheme. Additionally, MANET-ESO primarily enhances trusted routing between sensors and gateways

but does not effectively address the hotspot problem caused by uneven energy consumption in multi-hop WSNs.

Building on the insights and limitations identified above, this paper introduces a new clustering scheme that integrates UAV-assisted data collection and WPT to address key challenges in WSN-based smart irrigation systems, including energy efficiency, hotspot mitigation, and network longevity, as outlined in the following contributions.

1. New clustering scheme: The proposed scheme divides the network into two distinct regions; standard nodes in the central region and advanced nodes in the outer region, further organized into four clusters. This design balances energy consumption and optimizes data aggregation.
2. UAV-assisted data collection and charging: the scheme leverages a UAV as a mobile sink to traverse the network, collect data from optimized clusters, and wirelessly charge helper nodes using WPT, thereby enhancing network longevity.
3. Hotspot problem mitigation: by optimizing data collection rates and adaptively selecting cluster heads based on available energy, the proposed scheme effectively reduces energy imbalances and extends the lifetime the network.
4. Performance evaluation through simulations: extensive simulations demonstrate that the proposed scheme outperforms conventional clustering and energy management techniques, achieving lower energy consumption, a reduced number of dead nodes, and improved network lifetime.
5. Application in smart irrigation: the scheme is applied to a smart irrigation system, where it maintains stable soil moisture levels and reduces water consumption by approximately 20% compared to conventional irrigation methods.

3. Methodology

As stated above, WSNs enable the collection of large amounts of data over wide areas but face challenges like the short lifetime of sensor nodes due to a reliance on batteries. Frequent battery replacement is cumbersome, while energy harvesting from sources like solar, though helpful, is variable and insufficient to meet high energy demands.

Another major issue in WSNs is the hotspot problem, where an energy imbalance occurs due to the increased energy consumption of nodes located in data hotspots. In WSNs, multi-hop communication is typically used, where distant sensor nodes pass data to the BS through intermediate nodes rather than transmitting directly. This causes sensors in proximity to the BS to transmit and receive several data to relay packets from farther sensors. As a result, the nodes located near the BS (red nodes) experience higher energy consumption and a shorter lifespan compared to other nodes, as shown in Figure 1. When hotspot nodes die, the BS no longer receives their data or the data they should relay, leading to network isolation [14].

Several solutions have been proposed to address energy limitations in WSNs, including WPT for direct node charging and the use of mobile chargers, such as UAVs, for short-distance wireless energy replenishment. Additionally, mobile sinks have been introduced to collect data from cluster heads rather than directly from all nodes, reducing the overall communication overhead. However, WPT suffers from low efficiency over long distances, mobile chargers are constrained by limited mobility and energy capacity, and while mobile sinks alleviate network congestion, they do not fully resolve the hotspot problem near cluster heads [25–31].

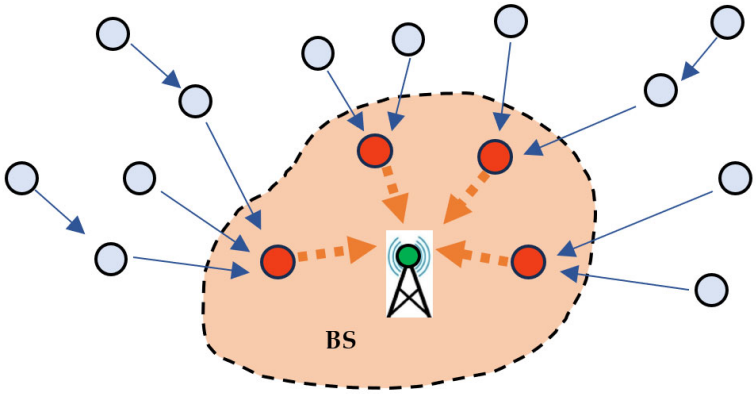


Figure 1. Hotspot example in a WSN.

3.1. The Proposed Scheme

To solve these issues, we propose a new scheme, with Figure 2 illustrating the network architecture. The network area is divided into two regions, the first region is at the center of the network and is represented as a circle area, and it contains types of nodes called standard nodes. The second region is at both sides of the circle and is divided into four clusters, two at each side of the circle. The proposed scheme encompasses three categories of nodes distinguished by their power levels: standard, advanced, and helper nodes. These sensor nodes are categorized based on their deployment method within the network, their specific locations, and their initial energy reserves. While standard and advanced nodes are placed randomly throughout the network, the helper nodes are positioned at fixed locations, as Figure 2 illustrates.

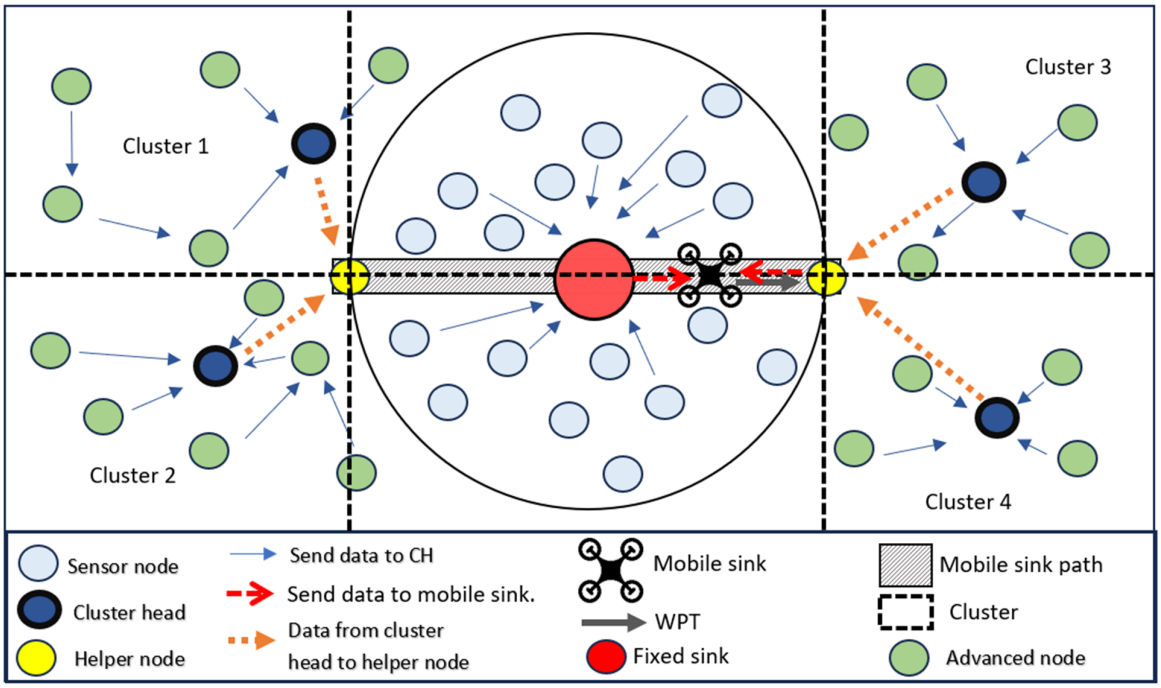


Figure 2. The network architecture of the proposed scheme.

The proposed scheme utilizes a UAV as a mobile sink, traversing the network to collect data from both the BS and helper nodes. Simultaneously, it wirelessly charges the helper nodes using WPT and adjusts data collection rates based on available energy, effectively mitigating the hotspot problem and enhancing overall network connectivity and performance. By optimizing the data collection rate and considering the energy levels in

both the sensor nodes and the mobile sink, the scheme efficiently addresses the hotspot issue. The employed mobile sink follows a predefined short path to collect environmental data from both helper nodes and the fixed sink, utilizing WPT through inductive coupling or magnetic resonance coupling methods. Hence, the proposed scheme reduces the necessity for sensor nodes to engage in a higher number of transmission hops.

Furthermore, to address energy imbalances, the scheme determines the optimal number of clusters by taking into account factors such as nodes per hop and available energy. It also selects a CH for each cluster. The mobile sink, typically a UAV like a quadcopter, follows its path, stops at each helper node, retrieves aggregated data, and provides energy as needed. After completing its route, the UAV returns to its starting point, where users can access the collected data and recharge or replace the UAV's battery for the next round.

This design choice which Figure 2 presents is based on the following criteria:

1. Energy distribution and load balancing: Dividing the secondary region into four clusters ensures that the data transmission burden is evenly distributed among the advanced nodes. A smaller number of clusters would lead to excessive energy consumption at a few cluster heads, while a larger number of clusters would increase communication overhead.
2. Efficient UAV-assisted data collection: Since the UAV follows a predefined path to collect data from helper nodes, having four clusters ensures optimal coverage without excessive flight distance. A different number of clusters could either increase the UAV's travel time and energy consumption or reduce its efficiency in gathering data.
3. Minimizing data transmission hops: The selected number of clusters allows for an optimal trade-off between the number of transmission hops and energy efficiency. Too few clusters would lead to long data transmission paths, while too many clusters would require more control overhead for managing additional CHs.

These design choices ensure improved network lifetime, energy efficiency, and stable communication, as demonstrated by the simulation results.

3.2. Energy Model

In the proposed scheme, a CH is selected based on energy availability, considering both data collection and energy received through WPT. The network operates in rounds, defined by the time it takes for the sink node to traverse the entire network. Data collection is dynamically adjusted by monitoring both available and consumed energy during each round. This subsection details the energy model used to calculate a node's available energy [13,14,25].

Solar energy is harnessed and utilized by the sensor nodes in this method. However, solar energy is subject to fluctuations and cannot be collected at night, necessitating a smart energy usage plan. To ensure the efficient and consistent utilization of solar energy over time, this study employs an energy allocation technique that evenly distributes available energy for each round among the sensor nodes if the allocated power to a node is P_{al} for a single round and the available power is P_{av}, which equals to P_{al}. Furthermore, the sink node has the capability to supply extra energy to the helper nodes. If the total power the sink node can provide to other nodes is P_{charge}, and this power is distributed equally among all helper nodes (m), then each helper node receives the power of P_{charge}/m. This additional power is added to the node's power P_{al}. In simple terms, the power available to a node for one round, P_{av}, is determined as follows:

$$P_{av} = \begin{cases} P_{al} + \frac{\eta P_{charge}}{m} & \text{for helper head node} \\ P_{al} & \text{otherwise} \end{cases} \quad (1)$$

where m is the number of helper nodes and η represents the efficiency of WPT. The power used by the sensor node can be categorized into two parts, power spent on the transmission and reception of data, and power used for essential operational tasks. Consequently, the total power consumption for the node during one round is as follows:

$$P_{Con} = P_{tx} + P_{rx} + P_{idle} \tag{2}$$

where P_{tx} is the power needed for data transmission, P_{rx} is the power needed for data reception, and P_{idle} is the power used for basic operations. Among these, P_{rx} and P_{idle} remain constant in each round, while P_{tx} can fluctuate based on the quantity of data being transmitted and the transmission distance. This relationship is expressed as follows:

$$P_{tx} = sP_1d^{\beta} \tag{3}$$

where β represents the path loss exponent, P_1 is the energy needed to send 1 bit of data over a 1 m distance, d stands for the node transmission distance, and s denotes the size of the data being transmitted. Since the node's energy consumption is directly linked to s, as mentioned in Equation (3), s should be adapted based on P_{av} to optimize energy efficiency, all while ensuring that the sensor node's power reserves are not depleted.

The UAV has a specific route it follows, as shown in Figure 2, visiting each helper node to gather data and provide energy. This process entails power consumption for its movement and data collection. Furthermore, when the UAV visits each helper node, it uses a short-range power transfer method, incurring power costs for takeoff and landing, as well as additional power consumption during hover time, primarily due to the time spent on recharging. If there are m helper nodes, this sequence of data collection, power delivery during takeoff and landing, and recharging occurs m times. Accordingly, the UAV energy model can be written as follows:

$$P_{UAV} = P_{travel} + m(P_{TL} + P_{d_coll}) + P_{charge} + P_{idle} \tag{4}$$

where P_{travel} is the consumed energy during UAV travel, P_{TL} represents the consumed energy during takeoff and landing processes, P_{d_coll} is the consumed energy during data gathering process, and P_{charge} is the provide energy to the helper nodes.

As the sink node follows a predetermined path in each round, the power consumed for its movement remains the same. Similarly, the power required for data gathering, take-off and landing, and other operational tasks remains constant. However, the variable P_{charge} is influenced by the number of helper nodes m. This P_{charge} is employed to replenish the power reserves of the m helper nodes.

3.3. Selecting Suitable Number of Clusters

In WSNs, the quantity of data transmission hops from the nodes decreases when there are more clusters, L, which conserves sensor node energy. However, this also means that the sink node, which needs to visit more helper nodes, consumes more energy. Consequently, the available energy P_{charge} for charging the helper nodes is diminished. Conversely, as L decreases, a considerable amount of energy is retained in the sink node, leading to an increase in P_{charge} but this results in more data transmission hops from the sensor nodes, potentially worsening energy imbalances. Hence, it is crucial to find the optimal value of L that ensures the optimal utilization of energy.

Let n represent the total number of sensor nodes, with p denoting the ratio of advanced nodes and f indicating the ratio of helper nodes. Advanced nodes start with a greater initial power reserve compared to standard nodes. Helper nodes are strategically placed

to minimize energy consumption within the network. Their primary function is to gather data from the closest CHs and relay it to the helper nodes and then to the mobile sink.

Assuming that the advanced nodes possess α times more energy than the standard nodes, the total initial power for the advanced nodes can be computed as:

$$P_{tot.adv} = n.p.P_{av}(1 + \alpha) \tag{5}$$

The collective initial energy of all helper nodes is represented as in Equation (5). Each individual helper node possesses v times more energy than a standard node. The total count of helper nodes and their combined initial energy can be expressed as follows:

$$m = n.f \tag{6}$$

$$P_{tot.helper} = m.P_{av}(1 + v) \tag{7}$$

The computed overall initial power for the three-tiered heterogeneous network, considering the modified scheme, is determined as follows:

$$P_{total} = n.P_{av}(1 - p - f) + n.p.P_{av}(1 + \alpha) + n.f.P_{av}(1 + v) = n.P_{av}(1 + \alpha.p + f.v) \tag{8}$$

The process of selecting CHs from the advanced nodes can be explained as follows: a cluster is formed using the advanced nodes, and the CHs are responsible for aggregating data from their cluster members and subsequently forwarding it to the nearest helper node then this helper node resends the collected data to the mobile sink. On the other hand, the standard nodes use the direct transmission to send their data to the fixed BS and will be deployed in circle zone, as shown in Figure 2. The proposed scheme seems to mitigate the issue of hotspots by fine-tuning data collection quantities and ensuring data collection remains within the available power range.

4. Results and Discussion

To evaluate the performance of the proposed scheme outlined in this paper, we conducted several simulations. Our proposed scheme was compared with the following approaches:

1. A conventional technique adapted for energy-harvesting nodes (fixed).
2. A technique for randomly selecting cluster heads along a predefined path (random).
3. The cluster configuration approach presented in [14].
4. Krishnamoorthy's scheme presented in [24].

The fixed technique involves the UAV identifying a CH at a predefined location with the shortest distance. In the random technique, a fixed number of CHs are chosen at regular intervals, commencing from random points along the UAV's path and are periodically reselected. This technique helps address energy imbalances by periodically changing cluster heads. In our simulations, we use β = 4, a transmission rate of 250 kbps, and a UAV speed of 16 m/s, as presented in [14]. Since we compare our results with those in [14], we adopt the same parameter values to ensure a fair comparison. Table 1 outlines the key parameters employed in the simulation.

Figure 3 illustrates the relationship between the number of dead nodes and the number of cluster heads for the considered schemes. In this figure, the fixed and random clustering schemes maintain a predetermined number of clusters, whereas the proposed scheme, Yoon's scheme [14], and Krishnamoorthy's scheme [24] dynamically adjust the number of clusters based on the network's energy conditions. Consequently, the proposed scheme and Yoon's scheme [14] yielded identical outcomes in certain scenarios due to their

energy-aware clustering mechanisms. However, Krishnamoorthy's scheme [24], which employs energy-aware routing, also demonstrated improvements in reducing power outages compared to fixed and random clustering but did not perform as efficiently as our proposed scheme.

Table 1. Used parameters.

Parameter	Value
No. of sensors	1000
Network area	100×100 m^2
Efficiency of WPT	50%
Transmission rate	250 Kbps
Start energy	0.5 J
β	4
UAV speed	16 m/s

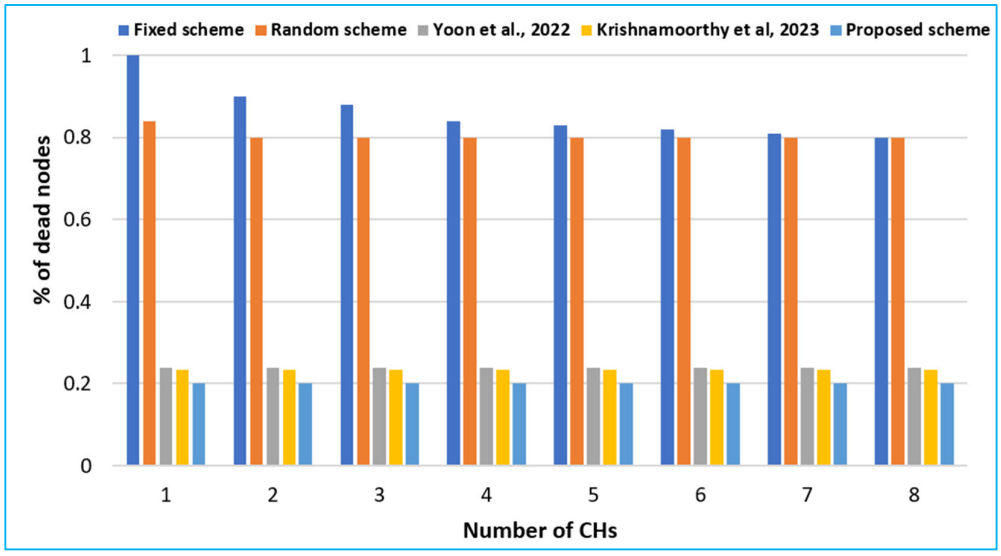


Figure 3. Number of dead nodes versus number of cluster heads for the fixed clustering, the random clustering, Yoon's scheme [14], and Krishnamoorthy's scheme [24].

There was a marginal increase in the number of nodes experiencing power outages as the number of clusters decreased in the fixed, random, and Krishnamoorthy's [24] techniques. This is attributed to the fact that a reduction in the number of cluster heads results in an increase in transmission hops, leading to higher energy consumption in data relay. The increased energy usage accelerates node depletion, particularly in hotspot areas where nodes relay data over multiple hops. While Krishnamoorthy's scheme [24] mitigates this effect by optimizing energy-aware routing, it does not incorporate UAV-assisted data collection or WPT, limiting its overall performance compared to the proposed scheme. Moreover, the proposed scheme achieves the lowest number of dead nodes, indicating that it has the longest network lifetime among all the considered schemes. For example, when the number of CHs is four, the percentage of dead nodes in the proposed scheme is 20%, whereas it increases to 88%, 80%, 24%, and 23.5% for the fixed clustering, the random clustering, Yoon's scheme [14], and Krishnamoorthy's scheme [24], respectively.

Figure 4 presents the data collection efficiency as a function of the number of cluster heads for the considered schemes. The results indicate that the proposed scheme achieves

the highest data collection efficiency, benefiting from UAV-assisted data gathering and adaptive clustering which optimizes data transmission and minimizes packet loss. In contrast, the fixed and random clustering schemes exhibit lower efficiency due to inefficient cluster head selection and increased node failures, which disrupt communication and reduce the amount of successfully collected data. For example, when the number of CHs is four, the amount of data collection in the proposed scheme is 16×10^6 bit, whereas it decreases to 7×10^6 bit, 6.9×10^6 bit, 14.7×10^6 bit, and 14.9×10^6 bit for the fixed clustering, the random clustering, Yoon's scheme [14], and Krishnamoorthy's scheme [24], respectively.

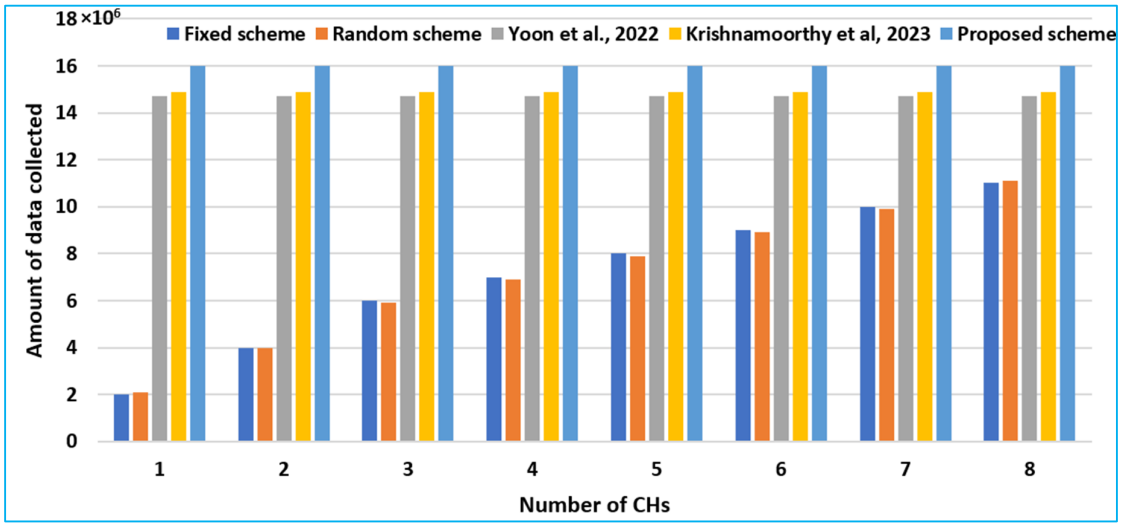


Figure 4. Amount of data collected versus number of cluster heads for the fixed clustering, the random clustering, Yoon's scheme [14], and Krishnamoorthy's scheme [24].

The fixed and random clustering schemes suffer from high packet losses due to inefficient CH selection and frequent node failures, leading to lower data collection efficiency. Yoon's scheme [14] improves efficiency through hierarchical clustering, but lacks UAV-assisted path optimization, which limits its performance. Similarly, Krishnamoorthy's scheme [24] enhances routing efficiency but does not dynamically optimize CH selection based on real-time energy conditions, making it less effective than the proposed scheme.

Figure 5 illustrates the proportion of energy consumption across all schemes. It is evident that the energy consumption increases as the number of nodes grows. However, the energy consumption of the proposed scheme is lower than that of the other schemes. This variation is primarily due to the smaller number of nodes experiencing blackouts in the proposed scheme. A reduced number of nodes experiencing blackouts mean that the nodes within hotspots must expend more energy since they need to relay data from other nodes. Additionally, the helper nodes consume more energy as they receive energy from the mobile sink and utilize it. Consequently, the proposed scheme exhibits lower energy consumption in contrast to the other schemes. For example, when the number of sensors is 400, the percentage of consumed energy in the proposed scheme is 66%, whereas it increases to 81%, 81.3%, 76%, and 74% for the fixed clustering, the random clustering, Yoon's scheme [14], and Krishnamoorthy's scheme [24], respectively.

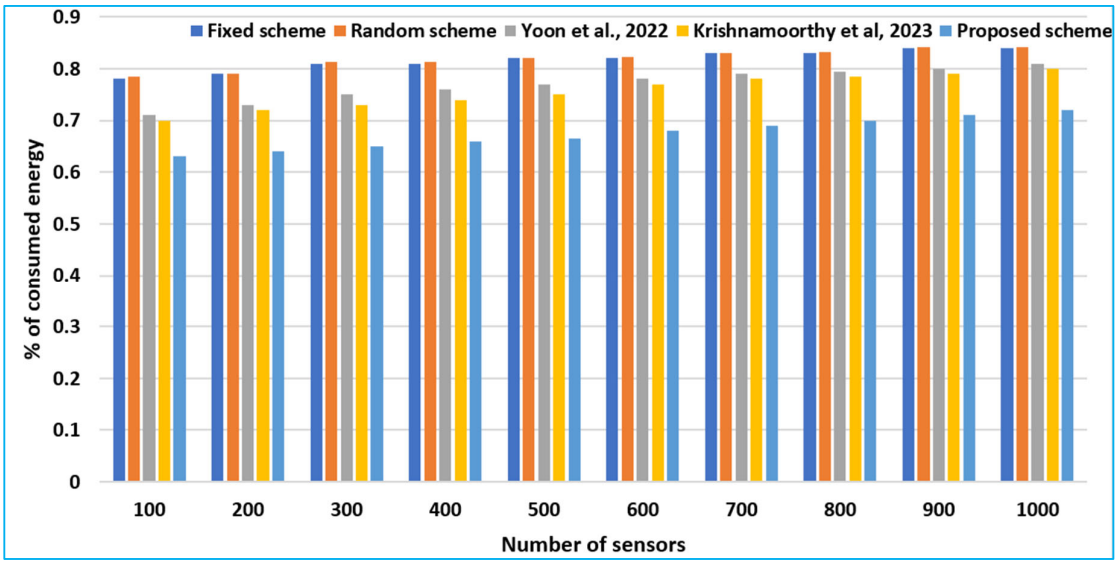


Figure 5. Consumed energy versus number of sensors for the fixed clustering, the random clustering, Yoon's scheme [14], and Krishnamoorthy's scheme [24].

Figure 6 presents the residual energy levels of sensor nodes across different simulation rounds for the five considered schemes: the proposed scheme, the fixed clustering, the random clustering, Yoon's scheme [14], and Krishnamoorthy's scheme [24]. The results demonstrate that the proposed scheme maintains the highest residual energy, outperforming all other approaches. Specifically, at the end of the simulation (round 300), the proposed scheme retains approximately 75.5% of residual energy, whereas Yoon's scheme [14] and Krishnamoorthy's scheme [24] retain 60% and 69%, respectively. In contrast, fixed clustering and random clustering exhibit a steeper decline, with only 25% and 29.5% remaining, respectively. This improvement is attributed to the proposed cluster formation and UAV-assisted WPT, which optimizes energy distribution and prevents the rapid depletion of nodes. Moreover, the proposed scheme minimizes transmission hops and optimizes the UAV's path, reducing energy consumption and achieving the highest residual energy level among the considered schemes.

Figure 7 compares the network lifetime among the considered schemes by presenting the first dead node (FDN), the half dead node (HDN), and the last dead node (LDN). The results indicate that the proposed scheme significantly extends the network lifespan as it achieves a slower rate of node depletion compared to other schemes. This enhancement is due to efficient cluster head selection, energy-aware data collection, and UAV-based wireless charging through an optimized path, which collectively mitigate the hotspot problem and prevent early node failures.

Figure 8 illustrates the throughput performance, measured as the total amount of successfully transmitted data across the five considered schemes. The results show that the proposed scheme achieves the highest throughput, ensuring more efficient and reliable data collection. Specifically, at the end of the simulation (round 300), the proposed scheme achieves approximately 4.3 Mbps, whereas Yoon's scheme [14] and Krishnamoorthy's scheme [24] attain 3.01 Mbps and 3.45 Mbps, respectively. In contrast, fixed clustering and random clustering demonstrate significantly lower throughput, with only 1.7 Mbps and 2.2 Mbps, respectively. The higher throughput in the proposed scheme is attributed to the adaptive clustering mechanism and UAV-assisted data gathering, which prevent network congestion and optimize data transmission efficiency. By reducing transmission hops and minimizing the communication overhead, the proposed scheme ensures higher

data delivery efficiency, making it a more robust solution for real-time and energy-efficient WSN-based smart irrigation systems.

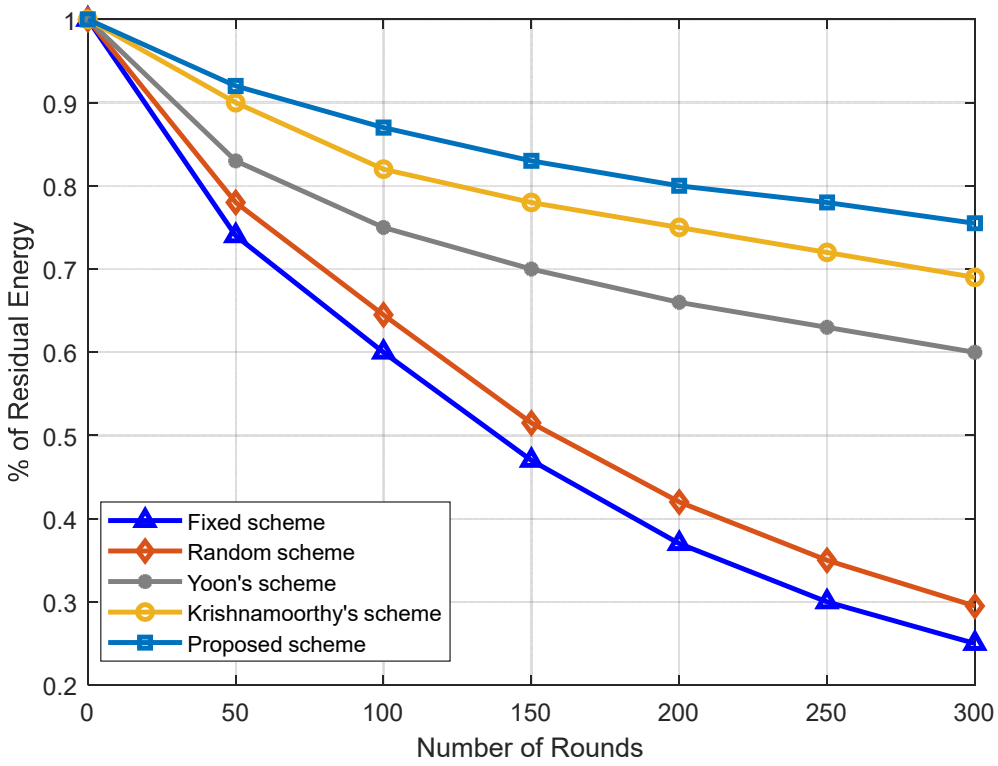


Figure 6. Residual energy against the number of rounds for the considered schemes.

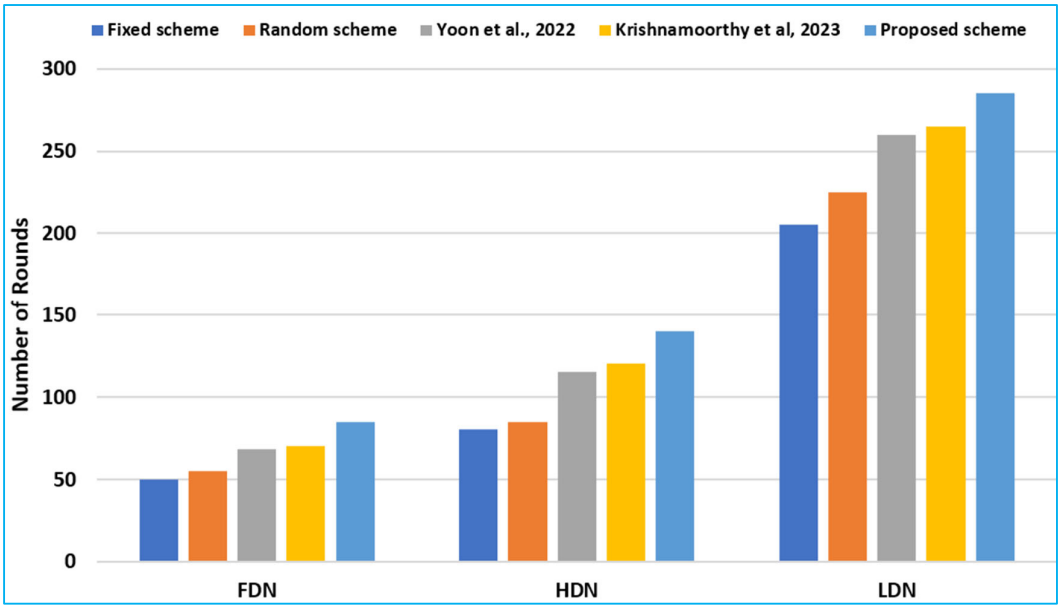


Figure 7. Network lifetime comparison for the fixed clustering, the random clustering, Yoon's scheme [14], and Krishnamoorthy's scheme [24].

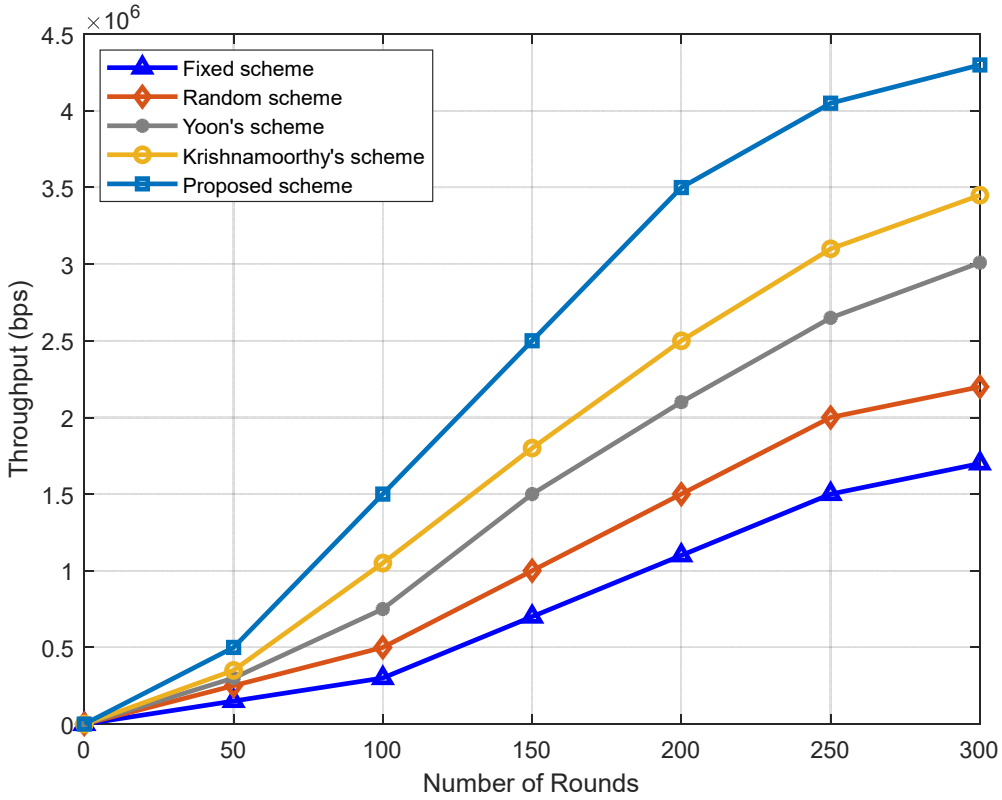


Figure 8. Throughput comparison for the considered schemes.

Table 2 summarizes the obtained results for the considered schemes, comparing key performance metrics such as the percentage of dead nodes, data collection efficiency, energy consumption, residual energy, network lifetime, and throughput. The results clearly demonstrate the superiority of the proposed scheme over traditional clustering methods, including fixed clustering, random clustering, Yoon's scheme [14], and Krishnamoorthy's scheme [24].

Table 2. Summary of obtained results for the considered schemes.

Performance Metric	Fixed Clustering	Random Clustering	Yoon's Scheme [14]	Krishnamoorthy's [24]	Proposed Scheme
% Dead nodes at CHs = 4	88%	80%	24%	23.5%	20%
Amount of data collection at CHs = 4 ($\times 10^6$ bit)	7	6.9	14.7	14.9	16
% Energy consumption	81%	81.3%	76%	74%	66%
% Residual energy at No. of round = 300	25%	29.5%	60%	69%	75.5%
FDN (Rounds)	50	55	68	70	85
HDN (Rounds)	80	85	115	120	140
LDN (Rounds)	205	225	260	265	285
Throughput at No. of round = 300 (Mbps)	1.7	2.2	3.01	3.45	4.3

The practical applications of this scheme are extensive. It can be employed in various scenarios, such as environmental monitoring, smart agriculture, and industrial automation. By enhancing the energy efficiency of sensor networks, it allows for extended operational

lifetimes, reduced maintenance, and more reliable data collection, which is invaluable in applications requiring long-term, autonomous data gathering and transmission. Finally, the proposed scheme not only contributes to improving the overall performance of WSNs but also has the potential to revolutionize their applicability in diverse real-world scenarios. In the following subsection we present a case study in which we apply the proposed scheme in the smart agriculture sector.

5. Case Study

This section examines the implementation of the proposed scheme in smart agriculture, aiming to advance sustainable and eco-friendly agricultural practices. This initiative is expected to enhance agricultural production efficiency and minimize resource wastage.

A. Problem Definition

The scarcity of water is one of the most important challenges facing the world. Therefore, water consumption and irrigation management are significant. The irrigation in conventional agriculture consumes a huge amount of water. Therefore, it has become necessary to propose smart irrigation techniques aimed at reducing water consumption without affecting the quality of agricultural crops. Using recent technologies such as WSNs can achieve this aim.

B. Network Model

Figure 9 presents the network model of WSN-based smart irrigation using the proposed scheme, which is a modified version of the network model presented in [8]. In this figure, the sensor nodes are strategically placed in agricultural fields to observe and gather a wide range of environmental and agricultural data. This includes parameters such as the air temperature, humidity, light intensity, soil conditions, and moisture levels, alongside the other relevant factors. At regular intervals, these sensor nodes send the collected data to CHs, which consolidate the information and transmit it to the BS and to the helper nodes, and it is then collected by the mobile sink. Subsequently, the data are forwarded to the control center and server through the internet. This collected data serves as valuable information for farmers, enabling them to make well-informed decisions to optimize crop yields and ensure the overall health of the farm.

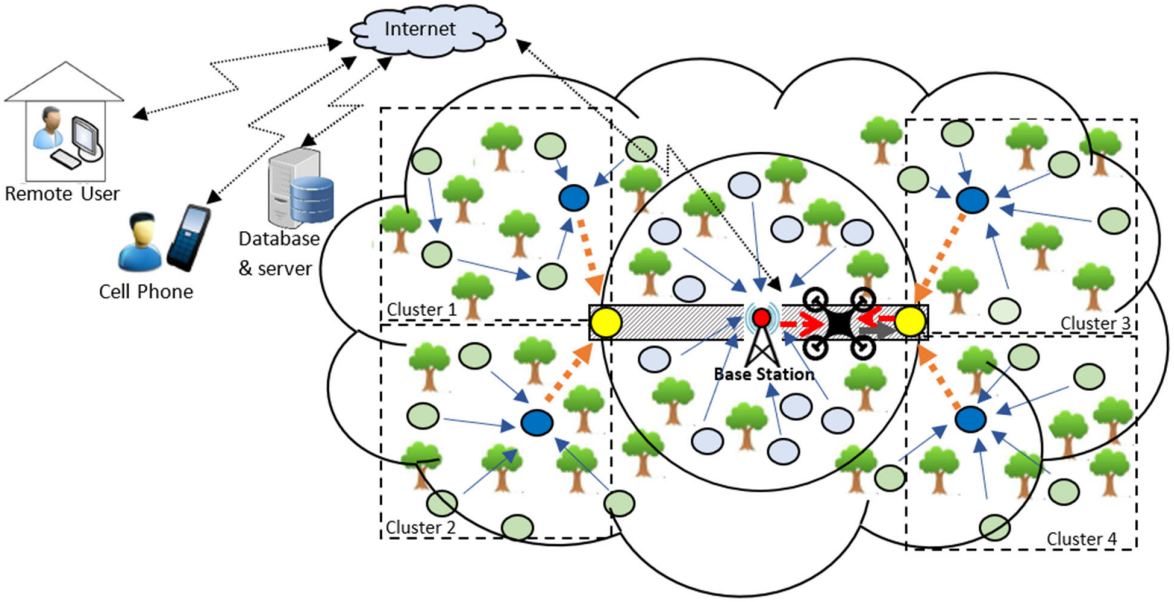


Figure 9. The network model of WSN-based smart irrigation using the proposed scheme.

Figure 10 illustrates a one-day contrast in water consumption between conventional irrigation, the smart irrigation method in [32], and smart irrigation using the proposed scheme. In this analysis, and according to Figure 6 in [32], the farmer opens the valve at the beginning of the day for one hour in the conventional irrigation method. Assuming a pump with a rate of 16,000 mL per hour, the conventional irrigation method requires 16,000 mL per day for irrigation. On the other side, based on the results presented in [32–34], the smart irrigation method operates four times a day, with irrigation durations varying depending on the applied scheme, as shown in Table 3 [34]. The irrigation times listed in Table 3 were determined using SAS 9.4M8 software [35], which calculates the optimal irrigation duration for each method. This duration represents the time interval between the activation and deactivation of the electric valve based on sensor readings.

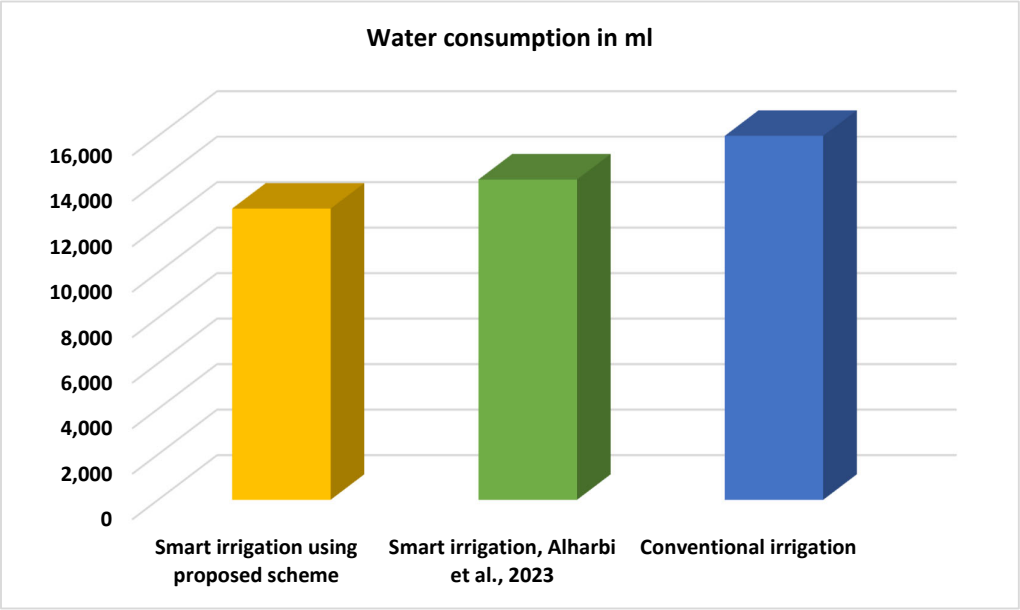


Figure 10. One-day comparison of water consumption between conventional, smart irrigation method in ref. [30] and proposed scheme.

Table 3. Irrigation time and water consumption comparison.

Irrigation Method	Irrigation Time
Conventional irrigation	60 min
Smart irrigation presented in [32]	4 × 13.2 min = 52.8 min
Smart irrigation using proposed scheme	4 × 12 min = 48 min

According to this figure, it is clear that the smart irrigation that uses the proposed scheme consumes less water when compared to the conventional irrigation method and the smart irrigation method in [32]. Specifically, it can save about 20% of consumed water when compared to other methods. Moreover, the conventional irrigation method exhibits fluctuating moisture levels, resulting in the soil being wet for brief periods and dry for extended durations. In contrast, the smart irrigation method ensures stable moisture levels, maintaining the soil at an optimal moisture content consistently. This stability in moisture levels is anticipated to enhance plant quality significantly when compared to the conventional irrigation method.

6. Conclusions

This paper proposed an energy-efficient clustering scheme for WSNs, integrating UAV-assisted data collection and WPT to overcome energy limitations and enhance network performance. The proposed scheme demonstrates superior performance in terms of network lifetime, data collection, and energy efficiency. Through various experiments and simulations, it has been established that the scheme effectively mitigates the hotspot problem by adjusting data collection rates based on available energy, resulting in stable moisture levels in smart agriculture applications. By categorizing sensor nodes into standard, advanced, and helper nodes based on their energy reserves, the proposed scheme optimally balances energy consumption and prolongs the network lifetime. The application of the proposed scheme in smart agriculture, as demonstrated by the case study, showcases its tangible benefits. The smart irrigation method, enabled by the scheme, exhibits stable moisture levels and consumes significantly less water compared to the conventional method. This not only ensures better plant quality but also aligns with sustainable agricultural practices.

While the proposed scheme enhances energy efficiency, network longevity, and data collection in WSN-based smart irrigation, it has certain limitations. Scalability constraints may arise in larger deployments due to an increased communication overhead and UAV energy limitations, potentially reducing the efficiency in extensive sensor networks. The energy constraints of the UAV present another challenge, as a single UAV may struggle to cover large networks effectively, leading to delays in data collection and energy replenishment.

To overcome these limitations, future research will focus on adaptive clustering mechanisms and multi-UAV coordination to improve scalability in large-scale deployments. Additionally, exploring adaptive mechanisms for UAV trajectories and charging strategies, considering dynamic changes in network topology and energy conditions, could further optimize energy efficiency and network performance. Integration of machine learning algorithms to predict and adapt to changing network conditions, as well as the exploration of alternative energy-harvesting technologies, could contribute to the scheme's resilience and versatility.

Author Contributions: Conceptualization, E.S.H.; Methodology, E.S.H.; Software, E.S.H.; Validation, A.J. and A.A.A.; Formal analysis, E.S.H.; Data curation, E.S.H.; Writing—original draft, E.S.H.; Writing—review & editing, A.J. and A.A.A.; Visualization, A.J. and A.A.A.; Supervision, E.S.H.; Funding acquisition, E.S.H., A.J. and A.A.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Acknowledgments: The authors gratefully acknowledge the funding of the Deanship of Graduate Studies and Scientific Research, Jazan University, Saudi Arabia, through Project Number: RG24-M028.

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

Abbreviations

The following abbreviations are used in this manuscript:

WSNs	Wireless Sensor Networks
UAV	Unmanned Aerial Vehicle
WPT	Wireless Power Transfer
IoTs	Internet-of-Things
EERPMS	Energy-Efficient Routing Protocol

CH	Cluster Head
EFCR	Energy-saving Fuzzy Clustering Routing algorithm
STP	State-transition probabilities

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