Adaptive Data Collection Using UAV with Wireless Power Transfer for Wireless Rechargeable Sensor Networks

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ABSTRACT
Wireless sensor networks (WSNs) are used to collect large amounts of data over a wide area. However, the sensor nodes used in WSNs have a short lifespan because they are generally battery-operated. Research is actively underway to increase the lifespan of WSNs via techniques such as energy harvesting and wireless power transfer (WPT). This study proposes a scheme for clustering and adjusting the WSN data collection rate to alleviate the hotspot problem and improve network connectivity. The proposed scheme is targeted at WSNs in which the sensor nodes harvest solar energy. In addition, an unmanned aerial vehicle (UAV) traverses along a given path and delivers energy to sensor nodes using WPT, while collecting data as a sink node. In this scheme, the number of cluster heads is determined by considering the number of nodes at each hop distance and the maximum amount of data that can be transferred with the available energy. Further, sensor nodes limit the amount of data they collect to reduce the relay load on intermediate nodes. To achieve this, nodes consider the amount of data transferred by parent nodes, especially nodes in the hotspot, and the number of child nodes. The sink node traverses along a given path, and collects the data accumulated in the cluster head while supplying its remaining energy to the cluster head. The amount of energy it transfers is determined by considering the number of cluster heads. Consequently, nodes in the hotspot are prevented from becoming blacked out from a lack of energy, and the energy harvesting efficiency is increased. Simulation results indicate that the proposed scheme reduces the number of blackout nodes in the hotspot areas near cluster heads. Furthermore, the data collection and monitoring performance increases with the increase in network connectivity.

INDEX TERMS energy harvesting, mobile sink, UAV, wireless power transfer, wireless sensor networks

I. INTRODUCTION
The recent development of the IoT and artificial intelligence has led to an increase in the need to collect a large amount of data. Wireless sensor networks (WSNs) are attracting attention as a technique for collecting large amounts of data over a wide area or in an area that is difficult for people to access. The sensor nodes used in WSNs have a short lifespan, as they are generally operated by battery. Therefore, to maintain the connectivity of the network, the battery of the node must be exchanged, or the node must be replaced with a new node. To overcome this, technologies for minimizing energy consumption are being actively researched [1]–[3].

One way to solve the problem of the limited energy of the sensor node is to use an energy harvesting sensor node that collects environmental energy (solar, wind, heat, vibration, etc.) to charge the battery [4]–[7]. Because this energy supply is greatly affected by changes in the environment, it is difficult to ensure a stable supply of energy to the sensor node. As recent sensors transmit large amounts of data in the form of photos and images, the transmission tends to rapidly consume energy, making it difficult to meet the energy requirements of the sensor node using only environmental energy. Therefore, a technique for stabilizing the energy supply and efficiently utilizing the collected energy
Recently, a technique for transmitting energy over long distances using wireless power transfer (WPT) was proposed [11], [12]. Based on this technique, methods for transmitting energy wirelessly from a base station to a sensor node or installing a charger in a car for charging while the car is in motion have been devised for WSNs [13], [14]. Although a high-end charger can be installed on vehicles, there are many restrictions in terms of the operating environment, as they can only travel in areas where there is a road. To solve this problem, an energy transmission technique using an unmanned aerial vehicle (UAV), such as a quadcopter, has recently been proposed [15]–[21]. Whereas a UAV moves through the air without being affected by the topography of the landscape, the weight of the equipment that can be mounted on it is limited due to transport weight limitations. Because of the battery limitations, the flight time is limited, which necessitates an efficient travel route or battery management scheme.

Another problem that affects WSNs is the hotspot problem. In this problem, an energy imbalance occurs when the energy consumption of nodes in hotspots where data are concentrated increases [22]–[24]. WSNs typically employ multi-hop communication. In this scenario, distant sensor nodes do not transmit data directly to the sink node; instead, they pass the data to the sink node through another node. Because of the multi-hop communication, sensor nodes closer to the sink node must send and receive more packets than other nodes to relay data from nodes farther from the sink node. Consequently, nodes closer to the sink node, i.e., nodes in the hotspot, consume more energy and tend to die earlier than other nodes. This results in the sink node not receiving the data possessed by the dead node, as well as the data that the dead node should relay, causing network isolation. Fig. 1 illustrates the hotspot problem.

A solution to the hotspot problem involves the use of a mobile sink, where the sink node directly visits the sensor nodes to collect data [25], [26]. In this method, as the sink node cannot visit all of the many nodes, clustering is generally used. The cluster head collects data from member nodes, and the sink node visits the head nodes only to gather the aggregated data in the cluster head. As the number of cluster heads increases, the number of member nodes in one cluster decreases. This can reduce the number of transmission hops to reduce energy consumption when nodes transmit data to the cluster head. However, the sink node has to visit more nodes, and more energy is required by the sink node, and the collection time also increases. In contrast, as the number of cluster heads decreases, the number of transmission hops in the node increases, which causes the sensor nodes to consume more energy. Therefore, an energy-efficient clustering scheme is required.

Although the usage of mobile sink nodes and clustering reduces hotspot problems, hotspot problems still exist in the cluster head and its neighboring nodes. If the cluster head does not work, the data collected thus far may be lost. If a neighboring node does not operate correctly, all data passing through that node may be lost, resulting in large data loss, which may even paralyze the entire cluster. Therefore, it is necessary to find ways to reduce the blackout of nodes in these hotspots [23], [24].

This study proposes a scheme for wireless rechargeable sensor networks (WRSN) to control the amount of data collected and to construct efficient clusters to increase the energy efficiency and the amount of data gathered at the sink node. To do so, nodes consider their available energy and the arrangement of sensor nodes. With this scheme, energy is supplied to the sensor nodes using solar energy and wireless power transmission. UAV traverses the network as a mobile sink and collects data while delivering energy to sensor nodes. In the proposed method, the most effective number of clusters is calculated by considering the amount of available energy according to the number of transmission hops from the sensor nodes, the energy consumed by the mobile sink, and the wireless power transmission energy. Using this, cluster heads are selected on the path of the sink node, and they form clusters. At this time, the hotspot problem is alleviated by determining the level of data collection by other nodes by considering the energy available in the cluster head and its neighboring nodes. By increasing the energy efficiency, the blackout of nodes is prevented, and the amount of data collected is increased.

The remainder of this paper is as follows. In Section II, we present the existing techniques related to WPT for WSNs. In Section III, we detail the proposed scheme. In Section IV, we show the performance evaluation of the proposed scheme, and we conclude this paper in Section V.

II. RELATED WORK
A. WPT FOR WSNs
WPT is a technique that transmits energy over a long distance and is used in various applications, such as portable devices, vehicles, and UAVs [11]. In WSNs, methods for using WPT to directly supply energy to sensor nodes having insufficient energy are studied as a means to solve the limited energy problem of sensor nodes [12].
First, there are techniques for transferring energy with a radio frequency (RF) method using a base station [12]. Whereas this method is characterized by a poor energy transfer efficiency due to the long distance between the node and the base station, it has the advantage of being able to charge multiple nodes simultaneously. Sangare et al. [14] developed a prototype of an RF WPT system to verify the actual performance in a system that delivered energy to a wireless sensor node using the RF method. They proposed a technique for efficiently supplying energy by adjusting the number of nodes, the distance between nodes, and the distance between the nodes and the charger to efficiently supply energy. Li et al. [27] proposed an optimization scheduling technique called EHMDP that was based on the Markov decision process and aimed to minimize data packet loss by considering node energy consumption and data queue status. This technique focuses on preventing packets from being lost beyond the limit of the queue in the case of an oversupply of energy. As a result, the throughput of the network increases, and the packet loss rate decreases. Ejaz et al. [15] proposed methods for arranging and calculating the minimum number of base stations to effectively transmit energy to all networks with the RF WPT from base stations in software-defined WSNs. Har [28] proposed a two-layer WPT method using clustering. In this scheme, the directional antennas were used to concentrate energy to cluster heads to increase the energy transfer efficiency. In addition, the cluster heads that received the energy again delivered energy to its surrounding nodes using unidirectional antennas.

The schemes for transmitting energy to the base station mentioned so far have low energy transmission efficiency [29]. Schemes for charging from within the network by mounting a wireless charger in a vehicle or UAV have been studied to solve this problem. These methods have the advantage of increasing energy efficiency by transferring energy over a short distance and collecting data from sensor nodes while charging them. However, because the charger has to visit nodes, it consumes energy by its movement and can only charge a limited number of nodes, which makes it difficult to use in large-scale WSNs.

One of the methods that uses a mobile wireless charger is the use of a vehicle [13], [31]. Guo et al. [13] proposed a technique for transferring energy to nodes and collecting data from anchor nodes using a vehicle equipped with a WPT system called SenCar as a mobile sink. In this technique, the node to be charged is selected, and the visit route is determined to increase the lifespan of the network by considering the battery capacity of the sensor node and the energy balance of all nodes. Tu et al. [31] proposed a technique to increase the network lifespan by efficiently transferring energy while a vehicle equipped with a wireless charger moves along a predetermined path and charges nodes. Unlike previous techniques, the movement path of the vehicle in this technique is set using a weighted traveling sales person (TSP) algorithm. This scheme considered not only the energy remaining in the node but also the travel distance of the vehicle. The charging method in this scheme was determined by considering the energy demand by the sensor node and the charging time.

Another method that uses a mobile wireless charger is the UAV [16], [17], [21], [32], [33]. Baek et al. [32] proposed a technique for determining the optimal UAV path and hovering time to maximize the amount of data collected as well as the energy level of the sensor node. They considered the energy consumed and collected by the sensor node and the limited energy of the UAV to determine the UAV path. The data were collected by the UAV and energy was supplied to sensor nodes using the RF method. Similar to the technique by Baek et al. [32], Xu et al. [17] proposed a method for finding the optimal path to increase energy efficiency by considering the speed and hover time of the UAV. The UAV is equipped with an RF-type charger and tours the sensor network to charge the sensor nodes. Griffin and Detweile [33] used the resonance coupling method instead of the RF method to transmit energy to a sensor node on the ground from a UAV in the air, demonstrating the application of the resonance coupling method. Unlike the above methods, Chen et al. [20] proposed a method of installing a charging pad inside the network to allow the UAV to be charged during the tour if it could not tour the entire network at once because of energy limitations. The location and number of pads required to increase energy efficiency were also suggested.

As mobile chargers cannot travel around all nodes to transmit energy in large-scale WSNs, techniques to compensate for this based on energy harvesting technology are being studied. Jadhav and Lambor [34] proposed a hybrid device design that simultaneously utilizes a solar panel for energy harvesting and an antenna for receiving energy via WPT with the RF method. Wang et al. [35] proposed a method for using WPT in an RF method in combination with energy harvesting in a network composed of energy harvesting sensor nodes and general battery-based nodes. In this technique, the high energy requirement of the cluster head, which was not satisfied by WPT, was supplemented using the energy harvesting method. Yi et al. [48] proposed a scheme for determining the number of clusters that increases energy utilization in an environment where nodes use solar energy and energy transmitted from UAVs as energy sources. In their scheme, when a UAV traversing a given path arrives at the current cluster heads, it transmits energy to them and receives data. When it arrives at the cluster head candidate area for the next round, it performs the cluster head election process in that area. The scheme determines the efficient number of cluster heads by considering the amount of data transmitted by the cluster heads, the solar energy, and the energy received via WPT.

Most of the techniques described above use an RF method with a fixed antenna, which has low energy transmission efficiency and is difficult to use in a wide-range network. In addition, the techniques are difficult to apply to networks with many sensors because the mobile charger has to visit all nodes. Although there are other methods that use a UAV, most
of them use an RF method to charge all nodes with a small amount of energy while passing over the nodes in a short time. Moreover, it is difficult to do so with large-scale sensor networks. Therefore, a technique that can be used in large-scale WSNs is required, and a technique that uses inductive coupling or magnetic resonance coupling method to improve energy transmission efficiency. In addition, because the mobile charger cannot visit all nodes in such an environment, a technique to extend the lifespan of the network by controlling energy consumption according to the situation is needed.

B. CLUSTERING FOR ENERGY HARVESTING WSNs

In the energy harvesting WSNs, sensor nodes harvest energy from the environment. As a result, they can operate indefinitely if their energy is managed precisely. In the energy harvesting WSNs, a new clustering scheme is required that is different from that of the traditional WSNs. This new scheme has to focus on reducing the energy consumption of sensor nodes. Researchers have proposed several clustering algorithms for energy harvesting WSNs [36], [39].

Voigt et al. [37] proposed the solar-aware LEACH (sLEACH) algorithm, which extends LEACH [38] to energy harvesting WSNs. In the sLEACH algorithm, solar-powered nodes are preferentially chosen to undertake the extra transmissions required from cluster heads. Han et al. [40] proposed a clustering scheme designed for energy harvesting WSNs. The clustering scheme considers the harvested energy to determine clustering and intercluster communication. It also adopts ant colony optimization for intercluster routing, and fuzzy logic for cluster head selection and cluster size allocation. Ren et al. [41] proposed the energy-efficient cluster head selection scheme (EECHS). EECHS additionally uses scheduling nodes, unlike other clustering schemes that solely utilize cluster heads and cluster members. These scheduling nodes monitor the energy state of other sensor nodes and select cluster heads based on the information obtained. In addition, it uses harvested energy efficiently by dynamically adjusting the transmission range of nodes according to the energy state.

The scheme proposed in this paper also adopts a clustering method in the energy harvesting WSNs. However, unlike the above schemes, because the mobile sink and WPT are used in the environment, the route of the mobile sink and the energy delivered through WPT are considered to construct efficient clusters.

C. MACHINE LEARNING FOR WSNs

Recently, with advances in artificial intelligence, researchers have applied machine learning (ML) to WSNs [42]–[45].

Kumar et al. [43] discussed the advantages and disadvantages of using ML in WSN. In addition, they applied ML in WSN for synchronization, congestion control, mobile sink scheduling, energy harvesting, and QoS, and also examined the limitations of ML in WSNs. Banoth et al. [46] proposed the dynamic mobile charger scheduling (DPMCS) scheme. DPMCS determines the schedule of a mobile charger using deep reinforcement learning in applications in which nodes request charging before their energy is depleted and the mobile charger charges them. It increases the lifespan of the WSNs by reducing the number of dead nodes and minimizing the moving distance of the mobile charger. Nayak et al. [45] examined the application scenarios of ML in WSNs. In particular, they focused on routing, which is the area where ML is most often applied.

WSNs using ML cannot produce stable and efficient results until the ML model has learned sufficiently because ML requires a long learning phase [43]. In addition, because much data are required, it is necessary to collect data over a long period. However, before collecting all the necessary data, the lifespan of the node may expire, and it may not be possible to collect the required amount of data. Unlike the schemes using ML, the scheme proposed in this paper can produce efficient results even when there is no time for learning or the data accumulated is not a lot. In the area targeted by our proposed method, the scheme proposed by Banoth et al. [46] uses ML to determine which node to charge and the route of the mobile charger. In contrast, our scheme uses a mobile charger that traverses a fixed route, and nodes that are not in the route exclusively use solar energy. Furthermore, as there is no learning stage, it exhibits stable performance from the beginning of operation.

III. CLUSTERING AND DETERMINING THE DATA COLLECTION RATE

This paper proposes a clustering and data collection rate determination scheme for energy harvesting WSNs. In this scheme, a mobile sink visits cluster heads to collect data and transfer energy to them via WPT with inductive coupling or magnetic resonance coupling methods. This reduces the blackouts of sensor nodes and increases the amount of data collected. The proposed scheme determines the efficient data collection rate by considering the energy available in the sensor nodes and the mobile sink. The sensor nodes that are powered by solar energy periodically collect environmental data, and a mobile sink traverses a given path proposed by Shin et al. [47] and collects the data from them. This scheme reduces the number of transmission hops from the sensor nodes. Further, to alleviate the energy imbalance problem, the most efficient number of clusters is calculated by considering the number of nodes per hop and the energy available. In addition, a cluster head is selected for the configuration of each cluster. The mobile sink node, which is a UAV such as a quadcopter, periodically traverses a predefined path and collects data by visiting the cluster heads, as in the method proposed by previous studies [48].

Because the cluster head consumes more energy than other nodes [23], [24], the sink node supplies the necessary energy to the cluster head via WPT. The UAV traverses a given path, stops at each cluster head, collects the data aggregated in the cluster head, and transfers energy. After the UAV traverses the route once, it returns to the starting point. There, the user retrieves the data collected by the UAV and recharges it or
The available energy during each round of each sensor node is determined by calculating the available and consumed energy during that time. This subsection describes the energy model for calculating the available energy of a node.

A. ENERGY MODEL OF A SENSOR NODE

In the proposed method, the cluster head is selected, and the amount of data collection is determined by considering the amount of energy available, data collection by the sensor node and the energy received through the WPT. For this, the period during which the sink node traverses the entire network once is set as one round, and the amount of data collected is determined by calculating the available and consumed energy during that time. This subsection describes the energy model for calculating the available energy of a node.

The sensor node of the proposed method harvests and uses the solar energy. Because solar energy shows large variations over time and is impossible to harvest during the night, a proper energy use plan is required [49]. To use this solar energy even over time without wasting it, various energy allocation techniques have been devised to allocate usable energy every time [50], [51]. The scheme proposed in this study applies this energy allocation technique [50] to allocate the energy available for each round to uniformly use the energy of the sensor node.

If a node is allocated energy equal to \( e_{\text{alloc}} \) for one round, the available energy \( e_{\text{avail}} \) is equal to \( e_{\text{alloc}} \). Meanwhile, the sink node may provide additional energy to the cluster head. If the total amount of energy that the sink node can deliver to other nodes is \( e_{\text{charge}} \), the transmission efficiency is \( \eta \), and if the energy is delivered equally to all cluster heads, the amount of energy delivered to one cluster head is \( \frac{\eta e_{\text{charge}}}{m} \), and the cluster head can use this energy in addition to \( e_{\text{alloc}} \). In other words, the energy \( e_{\text{avail}} \) that a node can use during one round is expressed as:

\[
e_{\text{avail}} = \begin{cases} e_{\text{alloc}} + \frac{\eta e_{\text{charge}}}{m} & \text{if the node is a cluster head} \\ e_{\text{alloc}} & \text{otherwise} \end{cases}
\]

(1)

The energy consumed by the sensor node can be divided into data transmission and reception energy and energy consumed for other basic operations. Therefore, the energy consumption, \( e_c \), of the node for one round is expressed as:

\[
e_c = e_{\text{Tx}} + e_{\text{Rx}} + e_{\text{idle}},
\]

(2)

where \( e_{\text{Tx}} \) is the energy required to transmit data, \( e_{\text{Rx}} \) is the energy required to receive data, and \( e_{\text{idle}} \) is the energy consumed for other basic operations. Of this energy for other basic operations, \( e_{\text{Rx}} \) and \( e_{\text{idle}} \) are fixed amounts of energy consumed during each round, whereas \( e_{\text{Tx}} \) may vary depending on the amount of data to be transmitted, which can be expressed as follows [52]:

\[
e_{\text{Tx}} = s \beta r^\alpha,
\]

(3)

where \( \alpha \) is the path loss exponent, \( \beta \) is the energy required to transmit 1 bit of data 1 m, \( r \) is the transmission distance of the node, and \( s \) is the transmission data size. Because the energy consumed by the node is proportional to \( s \), as in (3) above, \( s \) must be adjusted according to \( e_{\text{avail}} \) to increase the energy efficiency within a range that prevents the depletion of the energy in the sensor node.

B. ENERGY MODEL OF A SINK NODE

The sink node must travel a predefined path and visit each head to collect the data and transfer energy. Therefore, the sink node consumes energy for movement and data collection. In addition, when the sink node visits each cluster head, it consumes energy for takeoff and landing while delivering energy to the head because it uses a short-range energy transfer method, and it consumes more energy while hovering due to the charging time. If there are \( m \) cluster head nodes, data must be collected, and energy must be delivered while taking off and landing \( m \) times. Therefore, the energy model of the sink node is expressed as follows [48]:

\[
e_{\text{full}} = e_{\text{move}} + m(e_{\text{land}} + e_{\text{Rx}}) + e_{\text{idle}} + e_{\text{charge}},
\]

(4)

where \( e_{\text{full}} \) is the total energy of the sink node, \( e_{\text{move}} \) is the energy consumed by movement, \( e_{\text{land}} \) is the energy for takeoff and landing, \( e_{\text{Rx}} \) is the energy for data collection, \( e_{\text{charge}} \) is the energy delivered to the cluster head, and \( e_{\text{idle}} \) is the energy for other operations. If (4) is rearranged for \( e_{\text{charge}} \), it is expressed as:

\[
e_{\text{charge}} = e_{\text{full}} - e_{\text{move}} - m(e_{\text{land}} + e_{\text{Rx}}) - e_{\text{idle}}.
\]

(5)
Because the sink node moves along a fixed path during each round, the movement energy is constant, and because the energy for data collection, the energy for take-off and landing, and the energy for other operations are constant, $e_{\text{charge}}$ changes with $m$. This $e_{\text{charge}}$ is used to charge the energy of $m$ cluster heads, as shown in (1). Fig. 3 shows the energy model of the sink node.

C. DETERMINING THE NUMBER OF CLUSTERS

In WSNs, the number of data transmission hops from the nodes decreases with an increase in the number of clusters $m$, which saves the energy of the sensor node; however, the sink node requires more energy with an increasing number of clusters, as it needs to visit more cluster heads. As a result, the energy $e_{\text{charge}}$ that can be used to charge to the cluster head is reduced. In contrast, when $m$ decreases, a large amount of energy remains in the sink node, thereby increasing $e_{\text{charge}}$, but the number of data transmission hops from the sensor nodes increases, which may worsen the energy imbalance problem. Therefore, it is necessary to determine the $m$ that allows the most efficient use of energy.

Yi et al. [48] used a naive technique that considered the energy of the head node in a situation where the transmission amount was fixed to determine $m$. However, in this study, the available energy and consumption of the head node and the node one hop away from the head node were considered to determine the number of clusters that would maximize the collected data in order to efficiently use the energy of the sensor nodes and the sink node. These two types of nodes are considered because the head node transmits the most data and consumes the most energy. Therefore, the amount of data collected in a cluster is bound to the energy situation of the head node. However, when the head node receives energy from the sink, it may have more energy available than do other nodes. In this case, the amount of data collected is bound to one-hop distance nodes that consume the most energy next to the head. To determine the effective number of clusters $m$, it is necessary to calculate the energy available to these nodes and determine the amount of usable data within this energy.

1) Calculating the number of nodes per hop distance in a cluster

Because the sensor node must deliver not only the data it collects but also the data it relays from other nodes, the number of nodes for each hop should be calculated to determine the energy consumed by each node in one cluster. When $n$ nodes were evenly distributed throughout the entire network and the hop distance was $h$ in one cluster, Son et al. [53] calculated the number of nodes $n_h$ for each hop in one cluster as follows:

\[ n_0 = 1 \]
\[ n_1 = \min \left( \frac{n}{m}, \rho \pi \frac{r^2}{h^2} \right) - n_0 \]
\[ n_2 = \min \left( \frac{n}{m}, \rho \pi \frac{2r^2}{h^2} \right) - (n_1 + n_0) \]
\[ n_3 = \min \left( \frac{n}{m}, \rho \pi \frac{3r^2}{h^2} \right) - (n_2 + n_1 + n_0) \]
\[ \vdots \]
\[ n_h = \min \left( \frac{n}{m}, \rho \pi \frac{hr^2}{h^2} \right) - (n_{h-1} + \cdots + n_2 + n_1 + n_0), \]

where $m$ is the number of clusters, $\rho$ is the node density (nodes/m$^2$), and $r$ is the node transmission distance. In summary, $n_h$ is expressed as follows:

\[ n_h = \begin{cases} 1 & \text{if } h = 0 \\ \min \left( \frac{n}{m}, \rho \pi \frac{hr^2}{h^2} \right) - \sum_{j=0}^{h-1} n_j & \text{if } h > 0 \end{cases} \]

2) Calculating the number of clusters

A node collects data from its descendant nodes and delivers them to the parent node, and these data must finally be delivered to the cluster head. Therefore, the amount of data that a node needs to transmit can be expressed as the sum of the data in the descendant nodes. The number of descendant nodes of a node within a distance of $h$ hops can be expressed using $n_h$ in (12). Therefore, the amount of data that this node needs to transmit is expressed as $\sum_{j=h+1}^{h_{\text{max}}} n_j$, which can be substituted into (3) to calculate the transmission energy $e_{\text{Tx}}$ consumed for one round as follows:

\[ e_{\text{Tx}} = s_d \left( \frac{\sum_{j=h+1}^{h_{\text{max}}} n_j}{n_h} + 1 \right) \beta r^\alpha, \]

where $s_d$ is the amount of data that one node collects in one round. This can be substituted into (2) to obtain the energy consumption $e_c$ for one round of a node within a distance of $h$ hops as follows:

\[ e_c = s_d \left( \frac{\sum_{j=h+1}^{h_{\text{max}}} n_j}{n_h} + 1 \right) \beta r^\alpha + e_{\text{Rx}} + e_{\text{idle}}. \]
In this scheme, the energy consumed by the node should be less than or equal to the available energy $e_{\text{avail}}$ because the energy consumed per round can only be as much as the available energy of the node. In other words, this should satisfy:

$$e_{\text{avail}} \geq e_c. \quad (15)$$

By substituting (1) and (14), the maximum amount of data that can be transmitted, which is:

$$e_{\text{alloc}} \geq s_d \left( \frac{\sum_{j=2}^{h_{\text{max}}} n_j}{n_1} + 1 \right) \beta r^\alpha + e_{\text{Rx}} + e_{\text{idle}} \quad (h > 0)$$

$$s_d \leq \frac{e_{\text{alloc}} - e_{\text{Rx}} - e_{\text{idle}}}{\left( \frac{\sum_{j=2}^{h_{\text{max}}} n_j}{n_1} + 1 \right) \beta r^\alpha} \quad \text{(16)}$$

$$s_d \leq \frac{e_{\text{alloc}} - e_{\text{Rx}} - e_{\text{idle}} + \frac{\eta e_{\text{charge}}}{m}}{\left( \frac{\sum_{j=1}^{h_{\text{max}}} n_j}{n_1} + 1 \right) \beta r^\alpha} \quad \text{(17)}$$

which can be calculated for nodes other than head nodes. In particular, the amount of data that a node at a one-hop distance from the head can transmit at one time, which we must consider to determine $m$, is expressed as

$$s_d \leq \frac{e_{\text{alloc}} - e_{\text{Rx}} - e_{\text{idle}}}{\left( \frac{\sum_{j=2}^{h_{\text{max}}} n_j}{n_1} + 1 \right) \beta r^\alpha} \quad \text{(18)}$$

As for the head node, as shown in (1), $e_{\text{avail}}$ differs from that of a general node owing to the energy delivered from the sink node. Considering this, the amount of data collected by the head node for one round is expressed as:

$$e_{\text{alloc}} + \frac{\eta e_{\text{charge}}}{m} \geq s_d \left( \frac{\sum_{j=1}^{h_{\text{max}}} n_j}{n_1} + 1 \right) \beta r^\alpha + e_{\text{Rx}} + e_{\text{idle}} \quad \text{(19)}$$

$$s_d \leq \frac{e_{\text{alloc}} - e_{\text{Rx}} - e_{\text{idle}} + \frac{\eta e_{\text{charge}}}{m}}{\left( \frac{\sum_{j=1}^{h_{\text{max}}} n_j}{n_1} + 1 \right) \beta r^\alpha} \quad \text{(20)}$$

As shown in (20), $e_{\text{charge}}$ must also be considered for the head node. This $e_{\text{charge}}$ depends on $m$, as shown in (5), where $e_{\text{charge}}$ must satisfy $e_{\text{charge}} \geq 0$ to prevent a shortage of the energy required for the operation of the sink node. When (5) is substituted into $e_{\text{charge}} \geq 0$, it is expressed as:

$$e_{\text{full}} - e_{\text{move}} - m(e_{\text{land}} + e_{\text{Rx}}) - e_{\text{idle}} \geq 0, \quad \text{(21)}$$

where it should be $m \geq 1$, if there is at least one cluster. When this is rearranged for $m$, $m$ should be in the range of

$$1 \leq m \leq \left[ \frac{e_{\text{full}} - e_{\text{move}} - e_{\text{idle}}}{e_{\text{land}} + e_{\text{Rx}}} \right]. \quad \text{(22)}$$

We selected the largest value of $m$ that maximizes the data transfer capacity $s_d$ of the one-hop neighbor node and head node of (18) and (20) within the $m$ range of (22) above, as the number of clusters in the next round. The maximum value $s_{\text{max}}$ of $s_d$ is selected as the amount of data collected in the next round. Algorithm 1 shows the process of calculating the number of clusters.

**Algorithm 1 Calculating the number of clusters**

1. for all $m$ within the range of (22) do
2. for all $h = 1$ to $m$ do
3. Calculate $n_h$ in (12)
4. end for
5. Choose maximum $s_d$ within the range calculated in (18) and (20)
6. if $s_d > s_{\text{max}}$ then
7. $s_{\text{max}} \leftarrow s_d$
8. $m_{\text{best}} \leftarrow m$
9. end if
10. end for
11. return $s_{\text{max}}$ and $m_{\text{best}}$

**D. SELECTING THE HEAD NODE**

Once the number of clusters $m$ is determined, the positions of the $m$ head nodes must be determined. In this scheme, considering the evenly distributed clusters and the energy imbalance problem, the position of the head node is arranged at regular intervals starting from a random position along the travel path of the sink node, based on the method proposed in a previous study [48], Fig. 4 shows the process of clustering.

The location determined in this manner should be transmitted by the sink node to the target nodes of the location. When the sink node arrives at the first node to collect data, it delivers the head location message, including the head node location information of the next round, the total number of clusters, and $s_{\text{max}}$ to neighboring nodes. The node receiving this message delivers the message to other nodes by broadcasting using the flooding method if it is a node along the travel path of the sink node. When a node receives the head location message for the first time, it delivers the message to other nodes by broadcasting. When such a message has already been received, the node ignores the message. When the nodes in the head candidate location receive the head location message, one of the most suitable nodes should be elected as the head.

In this scheme, the head selection message is exchanged between the nodes in the corresponding location, among which the closest node $v_i$ with an expected data transfer amount $s_i$ greater than or equal to $s_{\text{max}}$ is selected as the head. When the amount of data transmission exceeds $s_{\text{max}}$, the energy charged from the sink node may exceed the battery capacity because of the high energy demand, whereas the amount of data collected decreases when it is less than $s_{\text{max}}$. If there is no $v_i$ with $s_i$ greater than $s_{\text{max}}$, the node with the largest $s_i$ among the nodes with $s_i$ less than $s_{\text{max}}$ is selected. This decreases the amount of data collected but allows the collection of the maximum amount of data within a range that does not cause a blackout of nodes. The process of selecting cluster heads in this manner is as follows:
1) Node $v_i$ in the head candidate location that has received the head location message calculates the estimated amount of data transfer $s_i$ using (20).

2) As a result of comparing this with the estimated amount of data transfer $s_{\text{best}}$ of the most suitable node so far, if $s_i$ is more suitable, $v_{\text{best}}$ and $s_{\text{best}}$ are updated, and the new $v_{\text{best}}$ and $s_{\text{best}}$ are included in the head location message.

3) When a head selection message is received, the $s$ value included in this message is compared with $s_{\text{best}}$, and when $s_{\text{best}}$ is updated, the head selection message is sent again with the new information.

4) If no head selection message is received for a certain period of time, $v_{\text{best}}$ is selected as the head.

5) Node $v_i$, selected as the cluster head, broadcasts a Routing Message that includes $v_i$ and $s_i$ to determine the data transmission amount and the route of the members, allowing the clusters to compose the minimum depth tree (MDT).

Through this process, a cluster head that increases energy efficiency is selected, and the data collected by the sensor node can be transmitted to the head using MDT. Algorithm 2 shows the head selection process.

E. DETERMINING THE AMOUNT OF DATA COLLECTED AT EACH NODE

After a cluster is formed, a cluster member node must transmit data within a range that does not exhaust the energy of the nodes in the transmission path from itself to the cluster head. In other words, nodes should limit the data transmission of descendant nodes to prevent them from exceeding the available energy. To do this, when each node receives a Routing message, it compares the $s$ included in it with its own $s_i$ calculated using (17). The smaller of the two is determined to be the amount of data that can be transmitted in this round, and it is sent in the Routing message. The node receiving this message can limit the amount of data transferred by itself and its descendant nodes within a range that prevents all nodes from exceeding the data transfer capacity of their parent node by repeating this operation. As a result, all nodes collect the...
The proposed scheme comprises two phases. In the first phase, the number of clusters is calculated, and in the second phase, the cluster heads are selected and the amount of data collected is determined. We analyze the complexity of these two parts.

1) Time complexity of calculating the number of clusters

The proposed scheme determines $m$ within the range of (22), as shown in Algorithm 1. The maximal $m$ in Algorithm 1 depends on the energy state of the UAV, but if there are only heads in each cluster, $m$ can be up to $n$. Thus, the first loop in line 1 of Algorithm 1 can repeat at most $n$ times. In line 2, $n_h$ is calculated by (12), which is repeated $m$ times. Because $m \leq n$, the loop in line 2 also repeats up to $n$ times. All other calculations can be calculated in constant time. Therefore, the time complexity of this algorithm is $O(n^2)$. In contrast, the scheme proposed by Yi et al. [48] can determine the number of clusters in constant time. However, although the time complexity of the proposed scheme is higher than that of Yi et al., this algorithm is performed at the base station or UAV and is performed only once per round. Therefore, it has little impact on the overall sensor network.

2) Control message complexity of selecting the cluster heads

Here, we analyze the control message complexity of Algorithm 2. This is the communication overhead of the network. In this algorithm, two types of control messages are used: head location message and head selection message.

When the UAV first arrives at the network, it floods the head location message to all nodes in its path. If the path length of the UAV is $l$, the area of the region where the nodes receiving this message are located is $lr$. The number of nodes in this area is $lr\rho$. Because $l$ is proportional to $\sqrt{n}$ and $r$ is a constant, the number of nodes in this region and the number of head location messages is $O(\sqrt{n})$.

The head selection message is sent at least once by the nodes in each cluster head candidate area to neighboring nodes, and it can be additionally transmitted when $s_{best}$ is updated. Although the node that has already received the head selection message may not send it, this message can be transmitted up to the maximum number of nodes in the cluster head candidate areas. As one cluster head candidate area is similar to a circle with radius $r$, the area of one candidate area is $\pi r^2$, and the number of nodes in this area is approximately $\rho \pi r^2$. Therefore, the total number of nodes in all the cluster head candidate areas is $mp\pi r^2$. However, as the update messages in lines 6 and 14 of Algorithm 2 can be retransmitted up to $\rho \pi r^2 - 1$ by the updated message transmitted by each node, the head selection message for a candidate area is at most $(\rho \pi r^2)(\rho \pi r^2 - 1)$, which is as many as can be transmitted. Therefore, the number of head selection messages transmitted in all $m$ areas is $n(\rho \pi r^2)(\rho \pi r^2 - 1)$, and the message complexity of this message is $O(m)$.

Comparing the complexity of the two messages, $O(\sqrt{n})$ and $O(m)$, it is clear that $O(\sqrt{n})$ is larger in a general environment. Thus, the control message complexity of the proposed scheme is $O(\sqrt{n})$. However, this algorithm is performed once per round, and the period of one round is much longer than the data transmission period. Therefore, the overhead of the control message has little effect on the
network lifespan. Considering the scheme proposed by Yi et al., their scheme selects heads by exchanging control messages between the UAV and candidate nodes when the UAV arrives in the candidate area, instead of flooding messages to the nodes in the moving path of the UAV. The complexity of this method is $O(m)$, and our proposed scheme has high message complexity compared to this. However, in Yi et al.’s scheme, the UAV visits both the current heads and the next round heads, whereas the UAV in our proposed scheme only needs to visit the current heads. Therefore, it consumes less movement energy and can charge the sensor nodes with more energy than Yi et al.’s scheme.

IV. PERFORMANCE EVALUATION

A. SIMULATION ENVIRONMENT

To analyze the performance of the scheme proposed in this study, we performed a number of simulations. We used SolarCastalia [57], which is a simulation tool designed for the solar energy harvesting WSN. We modified the original SolarCastalia to add the movement of the UAV, energy allocation, and WPT. For the amount of harvested energy used in the simulation, we used data we had actually measured for seven days. The proposed scheme was compared with 1) the conventional technique modified to fit the energy harvesting node (fixed), 2) a technique for randomly selecting cluster heads in a given path (random), 3) the cluster configuration method proposed by Yi et al. (Yi) [48], and 4) the clustering using harmony search proposed by Son et al. (Son) [53].

The fixed technique is a method in which the UAV finds the cluster head at a predetermined location with the shortest distance. The random technique is a method in which a fixed number of cluster heads is selected at regular intervals starting from random positions in the path of the UAV, which are reselected periodically. This technique alleviates the energy imbalance by periodically changing the cluster head. The Yi method determines the number of clusters by considering the energy status of the mobile sink node and the amount of data collected, and it selects cluster heads based on the number of clusters in the same manner as the random technique. The Son method configures a cluster using harmony search and elects cluster heads to be visited by the UAV using several parameters such as energy variance, the number of neighbor nodes within 1-hop distance, and hop counts. Although this scheme is an efficient clustering technique, the clustering overhead is relatively high. This technique increases the energy efficiency by selecting an efficient number of clusters. In all of these techniques, when the mobile sink arrives at the cluster heads, the remaining energy of the mobile sink is evenly distributed between the cluster heads.

Node deployment has a large impact on simulation results [54]. To minimize this impact, we generated several node deployment datasets in advance and applied the same datasets to each scheme to perform accurate simulations. To generate the empirical dataset to deploy sensor nodes, we took 2D random values on the X–Y plane generated by Mersenne Twister [55], which is a pseudorandom number generator (PRNG) widely used in many simulators.

We assumed that DJI Phantom 3 [56] was used as the UAV, and its specifications were used for the simulation. The UAV has a wireless charger and a Zigbee module for communication with the sensor node. The maximum flight time of the UAV in the original specifications is 25 minutes. However, in the simulation, we set it at 20 minutes considering the weight of the wireless charger and communication module. In addition, the UAV needs to stay at a sensor node for a long time compared to general data communication because it has to transmit energy during data communication with the node. For this reason, when transmitting data and energy, to reduce hovering energy, it lands on the corresponding node. Consequently, additional take-off and landing energy is consumed when visiting a node.

For each scheme, the simulation was conducted for approximately 7 days (168 rounds), and the average value was used after repeating the experiment 20 times. The first round starts at 8 am. Table 1 shows the main parameters used in the simulation.

![Table 1. Simulation Parameters.](image)

B. SIMULATION RESULTS

1) Performance analysis according to changes over time

Fig. 5, 6, and 7 show that the change in the number of blackout nodes, the amount of data collected by the mobile sink node, and the total amount of residual energy of all sensor nodes, respectively, measured over seven days. In general, because the nodes are charged using solar energy during the day, there are few blackout nodes with a large amount of...
data collected. In contrast, during the night when there is no sun, the number of blackout nodes increases when a large amount of data is collected, as no energy is transferred to the nodes. The proposed scheme, however, limits the amount of energy that can be used for each round by applying the energy allocation technique. This results in fewer blackout nodes occurring even during the night. Therefore, an almost constant amount of data is collected in the proposed scheme, unlike other schemes at any time. In addition, the Yi, Son, and proposed schemes collect more data than the fixed or random scheme by adjusting the number of clusters properly. Further, it can be seen that the proposed scheme collects more data than the Yi scheme, which is another technique for controlling the number of clusters, and the Son scheme for efficient clustering, by adjusting the data collection rate.

On the other hand, we can see that the amount of data collected increases sharply in the morning for all schemes. This is because the nodes in the hotspot area are in a blackout state while other nodes are operating during the night. Then, in the morning, the network connectivity increases rapidly as the blackout nodes resume operation. However, as the evening approaches, the amount of data collected gradually decreases because the nodes in the hotspot area become blackout one after another. The proposed scheme collects a steady amount of data regardless of the time with efficient energy usage.

In Fig. 7, we can see that, at the beginning, the total residual energy of the proposed scheme decreases drastically. This is because the proposed scheme adjusts the data collection rate according to the available energy, so that more of the abundant energy at the beginning of the network is consumed for data collection. After 150 rounds, all schemes converge and exhibit a similar pattern, but the proposed scheme is slightly lower. This is because more nodes in the hotspot of the proposed scheme are alive than in other schemes. Therefore, nodes outside the hotspot area consume more energy to collect and transmit data and, as a result, more data can be collected compared to other schemes.

2) Performance analysis according to changes in the number of clusters

Fig. 8, 9, and 10 show the number of blackout nodes, the amount of sensing data, and the amount of data collected by the mobile sink, respectively, according to the number of clusters. In this simulation, the fixed, random, and Son schemes created the specified number of clusters, and the number of clusters was changed adaptively according to
the energy situation of the network for the Yi technique and the proposed scheme. Therefore, the Yi and proposed schemes have the same results in all these experiments. There were slightly more blackout nodes as the number of clusters decreased for the fixed and random schemes. This is because, when there are fewer heads, the number of transmission hops increases, which consumes more energy in the data relay. This is due to the increased energy consumption of the nodes following an increase in the data transmission hops from the sensor nodes.

In Fig. 9, whereas the amount of data sensed by the sensors did not change significantly depending on the number of clusters, the amount of data collected by the mobile sink showed a great difference in Fig. 10. When the number of clusters is small, data from many nodes are concentrated on a small number of cluster head nodes, resulting in blackouts of the nodes around the cluster heads due to the hotspot problem. As a result, even if the sensor nodes perform a lot of sensing, only a small amount of data seems to reach the cluster head node as the path to deliver the data is cut off. Compared with other schemes, including the Yi and Son schemes, the proposed method had fewer blackout nodes with a greater amount of successfully collected data. The proposed scheme appears to alleviate the hotspot problem by adjusting the amount of data collection and by collecting data within the available range of energy.

3) Performance analysis according to changes in the number of nodes

Fig. 11, 12, and 13 show the number of blackout nodes, amount of sensing data, and amount of data collected by the sink node in different cases. The proposed method appears to have fewer blackout nodes and more data collected by the sink node as the number of nodes increases.

Fig. 9. Comparison of amount of sensed data according to the number of clusters.

Fig. 10. Comparison of amount of gathered data according to the number of clusters.

Fig. 11. Change in the number of blackout nodes according to the number of nodes.

Fig. 12. Comparison of amount of sensed data according to the number of nodes.

Fig. 13. Comparison of amount of gathered data according to the number of nodes.
sensor nodes, respectively. In Fig. 11, the number of blackout nodes increases with the number of nodes for all techniques except the proposed scheme because the more nodes there are, the more data need to be relayed. However, in the proposed scheme, the number of blackout nodes increases less than the other schemes because the data collection rate is adaptively adjusted to prevent hotspot problems. As shown in Fig. 13, the amount of data collected did not increase significantly compared to the increase in the number of nodes because as the number of nodes increases, the hotspot problem also increases. On the other hand, note that the amount of data collected in the proposed scheme was also not significantly affected by the increase in the number of nodes because, unlike the other methods, the data collection rate is adaptively adjusted to prevent hotspot problems. As a result, the proposed scheme collected much more data than the other schemes. Therefore, the proposed scheme has better scalability than the other methods by adjusting the data collection rate and the number of clusters effectively according to the change in the number of nodes.

Fig. 14 and 15 show the average energy consumption and fairness index [58] according to the change in the number of sensor nodes, respectively.

In Fig. 14, the average energy consumption of all schemes decreases as the number of nodes increases. As seen in Fig. 11, the number of blackout nodes increases with the number of nodes; thus, the amount of consumed energy also decreases. However, we can see that the proposed scheme consumes more energy than other methods even when the number of nodes is small. This is because the proposed scheme adaptively adjusts the data collection amount to collect more data if the nodes have sufficient energy. Although the number of nodes is large, the proposed scheme shows relatively stable energy consumption compared to the other schemes. This is because the number of blackout nodes is small compared to the other schemes. Consequently, the proposed scheme consumes a relatively steady amount of energy compared to the other schemes regardless of the change in the number of nodes.

Fig. 15 shows the fairness index of the consumed energy [58]. In all schemes, it can be seen that the fairness index increases with the number of nodes. However, the fairness index of the proposed scheme is approximately 5% smaller than that of the other schemes. This is because the number of blackout nodes in the proposed scheme is small. The fewer blackout nodes there are, the more energy the nodes in the hotspot will inevitably consume because they have to relay more data from other nodes. In addition, in the case of the cluster heads, more energy is consumed because they receive energy from the UAV and use it. As a result, the fairness index of the proposed scheme is lower than that of the other schemes.

4) Performance analysis according to changes in the node density

Fig. 16, 17, and 18 show the number of blackout nodes, amount of sensing data, and amount of data collected by the UAV, respectively, according to the changes in the density of the sensor nodes.

As the density of the nodes decreases, the number of transmission hops increases, resulting in the sensor nodes using more energy to relay data. Therefore, in Fig. 16, it can
scheme effectively prevented the blackout of nodes, allowing data collection evenly from the entire network.

V. CONCLUSIONS

In this study, we proposed a scheme for increasing network connectivity and data collection by configuring a cluster and adjusting the amount of data to be collected. In the proposed scheme, UAVs equipped with a WPT system are used as mobile sinks to collect data while delivering extra energy in WSNs consisting of energy harvesting sensor nodes. Further, the number of clusters is determined by considering the node arrangement, the energy transferred by the UAV, and the available energy of the sensor nodes for one round. In addition, considering the number of nodes at each hop distance according to the number of clusters, each node adjusts the amount of data it collects so that the cluster head and 1-hop distance nodes do not become blacked out. Then, by selecting the cluster head at regular intervals, the hotspot problem is alleviated by reducing the number of transmission hops and the energy imbalance of the sensor nodes. Simulation results show that the proposed technique effectively suppresses the occurrence of blackout nodes and increases the amount of data collected regardless of any change in the number or density of nodes. In particular, by limiting the amount of data collected from member nodes, the cluster heads and their neighbors are prevented from becoming blacked out and, as a result, data are collected evenly from the entire network.

However, although the proposed scheme exhibited good performance in a given environment, it has the disadvantage that it can be applied only when the UAV traverses a fixed route. In future work, it will be modified to determine the optimal path for the UAV, which will make it more energy efficient.

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