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A Hybrid MCDM and Meta-heuristic-based Approach for Energy Efficient Routing in Wireless Sensor Networks

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Abstract

The energy-constrained WSNs consist of sensor nodes to be discriminated by multi-criteria which are mutually contradictory each other. Therefore, developing a clustering scheme blending these multi-criteria comprehensively is of particular importance for energy-constrained WSNs. However, most of the latest works have focused on exploiting individual intelligent optimization algorithms and little effort has been made on integrating Multi-Criteria Decision Making (MCDM) approach with the meta-heuristic algorithm. In this paper, we propose a novel clustering scheme using Adaptive Fuzzy C-Means (AFCM) and an improved Ant Lion Optimization (ALO) approach. This scheme first divides the whole network into k clusters using the AFCM algorithm. After that, an improved ALO is applied for each cluster to select the optimal Cluster Head (CH) nodes. At this time, this ALO prescribes a new multi-criteria based fitness function based on the weights of six multi-criteria assigned by Fuzzy Cognitive Network Process (FCNP) and made compensation with Variable Weight Analysis (VWA). Extensive simulation results reveals that the proposed scheme achieves a superior energy consumption balance, thus extending the network lifetime up to 272.9%, 116.6% and 109.2% compared to LEACH, ALOC and K-LionER schemes, respectively.

Keywords: Wireless sensor network; Adaptive fuzzy c-means; FCNP; VWA; ALO; Hybrid FCNP-VWA-ALO.

Introduction

WSNs are one of the key technologies for realizing the Internet of Things (IoT) and have been widely applied in various fields such as environmental monitoring, medical assistance, target tracking, military reconnaissance, precision architecture, and smart home, etc. [1-4]. A WSN, which consists of a number of low-power sensor nodes powered by batteries, usually collects the required information in a distributed or a self-organizing manner and transmits it to the base station (BS). Therefore, developing routing protocols that maximize network lifetime by increasing energy efficiency during the collection of sensor data is one of the most important and urgent challenges [1-7]. The most efficient routing approach for data collection in WSNs is the cluster-based approach [2]. The sensor nodes of WSNs are discriminated by several multi-criteria such as residual energy, distance to BS, energy consumption rate, and node neighboring degree [8]. Hence, a number of energy efficient cluster-based routing protocols have been developed that comprehensively consider these mutually contradictory multi-criteria. The typical algorithms which were used to comprehensively consider multi-criteria include fuzzy logic, MCDM, meta-heuristic optimization algorithm, and the combination of the above approaches.

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Fuzzy logic is to introduce the concept of fuzziness to multi-valued logic [9]. Fuzzy logic-based system can effectively select CH nodes and next relay CH nodes. In addition, it facilitates fuzzy representation of various criteria such as more energy and less distance, taking into account the various criteria which discriminate sensor nodes comprehensively. Thus, a number of cluster-based routing protocols using fuzzy logic have been developed so far [10-12].

MCDM approach is mainly used to evaluate the completed alternatives defined by several criteria or factors [13]. It can be seen that the MCDM approach can be used as a powerful tool in the design of cluster-based routing protocols that entail the most suitable CH node for the sensor nodes and the most appropriate next-hop CH node selection for relay data transmission from the selected CH nodes to BS. Thus, recently, there has been an active research effort to exploit MCDM approaches in cluster-based routing. Consequently, routing protocols using individual MCDM approaches such as AHP [14-16], VIKOR [13], ELECTRE [17], TOPSIS [18], PROMETHEE [19], [20] have been reported. To efficiently cope with various situations of WSNs, the results of the studies that have introduced the integrated MCDM approaches blending a MCDM approach with an another MCDM approach are also reported. Recently, the research results of further improving of charging performance by introducing these integrated MCDM approaches such as FAHP-VWA-TOPSIS [21], FAHP-VWA-Q-learning [22], FCNP-TOPSIS [23], FCNP-Q-learning [24], FCNP-VWA-PROMETHEE [25], have been reported for efficient charging scheduling of wireless rechargeable sensor networks (WRSNs). On the other hand, meta-heuristic optimization algorithms are usually based on the natural law of "the survival of the fittest" and embody the evolution of organisms through selection and mutation [28]. These meta-heuristic optimization algorithms are widely used as techniques to obtain optimal solutions for clustering and routing of WSNs. The examples of meta-heuristic optimization algorithms that have been widely applied in WSNs are grey wolf optimization (GWO) [26], ant lion optimization (ALO) [27], emperor penguin optimization (EPO) [28], etc. In addition, recent studies have also reported further improvements in the performance of cluster-based routing protocols in WSNs by blending fuzzy logic, MCDM, and meta-heuristic intelligent optimization approaches [10], [11], [29], [30].

The goal of cluster-based routing optimization is to maximize the energy consumption balancing among nodes by taking into account the various criteria in the whole process of clustering routing while maintaining stability, reliability and connectivity of network, and thus to extend network lifetime as much as possible. However, existing cluster-based routing protocols exploit either individual MCDM approaches or fuzzy logic or meta-heuristic optimization algorithms in the CH node selection of clustering stage. Clustering routing is usually performed in two stages: clustering phase and data transmission phase. In the clustering phase, the CH node is selected and CM nodes are enlisted in the selected CH nodes to form clusters, while in the data transmission phase, the sensed data is sent to the BS in a single or multi-hop mode. Hence, some researchers have proposed approaches that use integrated MCDM or mixed intelligent optimization in clustering phase and use meta-heuristic optimization algorithm in routing tree construction phase for data gathering.

The main objective of this work is to develop a cluster-based routing protocol that can maximize network lifetime by utilizing a hybrid FCNP-VWA and ALO in combination with the AFCM algorithm in the clustering phase of WSN routing protocol, while maximally balancing and efficiently utilizing the limited energy of all sensor nodes. To our knowledge, this is the first study to exploit a hybrid FCNP-VWA and ALO in CH node selection in clustering phase of cluster-based routing. The main contributions of this study are as follows.

- ·An improved ALO is proposed, in which its optimization ability is improved by defining a new multi-criteria based fitness function of ALO using the weights of six multi-criteria assigned by FCNP and made compensation by VWA.
- ·A hybrid FCNP-VWA and ALO-based clustering scheme has been proposed. It divides the whole network into k load balancing clusters by the AFCM algorithm and selects the optimal CH nodes for each cluster with the improved ALO.
- ·Extensive experiments have been carried out to verify the superiority of the proposed protocol in comparison with other existing schemes.

The rest of this paper is organized as follows. In Section 2, related previous works are discussed. The network model and energy consumption model are described in Section 3. Section 4 presents the proposed protocol. The results of extensive simulation of the proposed protocol and its analysis are presented in Section 5. Finally, Section 6 concludes the paper.

Related works

Here, we briefly review previous works on clustering and routing approaches using fuzzy logic, MCDM approaches and meta-heuristic optimization algorithms. In [12], the authors proposed clustering scheme by selecting the optimal CH node with fuzzy logic using various criteria. Lekhrai et al. [13] used seven multi-criteria to select CH node with VIKOR to perform clustering. In [14-16], the energy-efficient routing approaches using AHP approach were proposed. In [17], the authors proposed a approach to select CH nodes with ELECTR-I using multi-criteria. Supriyan et al. [18]

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proposed a approach to select CH nodes with TOPSIS using multi-criteria. In [19], the authors proposed clustering approaches using individual MCDM such as AHP, TOPSIS, and PROMETHEE with 16 mutually contradictory multi-criteria to balance load and energy consumption in clustering.

A number of clustering and routing schemes using meta-heuristic optimization algorithms have also been developed. In [31], the authors proposed a scheme to select CH nodes with improved GWO using four multi-criteria to calculate the fitness value. However, this scheme equally assigns all the weights of four multi-criteria to 0.25 in the fitness value calculation. Zhao et al. [32] proposed a scheme to select CH nodes by GWO that calculates the fitness value with two criteria of residual energy and distance (distance to base station and distance to prey, i.e., CH node). This scheme dynamically changes the weights determined by the fitness value of nodes to improve the optimal performance of GWO and ensure the optimal CH node selection. The approach proposed in [33] performs feature selection using GWO and combines it with particle swarm optimization (PSO) to update the position of each wolf, thus improving the performance. In [34], the load balancing clustering is performed with improved GWO using five multi-criteria, such as network lifetime, number of dead CH nodes, number of dead gateways, number of sensor nodes, and energy consumption. Jayashree et al. [35] proposed a swarm intelligence-based routing scheme using clustering by K-means and CH node selection by GWO. In [36], the authors attempted to achieve the goal of distance reduction, power stabilization and node delay minimization by clustering the sensor nodes with ALO and by reducing network overhead dynamically in such a way that find the shortest path with geography-enhanced energy efficient routing (GEAR-R). CH node selection is modeled as a fitness function of ALO to enhance the network performance [52]. The authors apply a discrete ALO to obtain the optimal data collection path for a mobile sink. The order that a mobile sink visits the selected CH nodes is calculated by this discrete ALO and collects their data. In [37] and [38], an energy efficient clustering routing scheme using hybrid K-means ant lion optimization algorithm is proposed. In these schemes, the entire network is divided into clusters using K-means algorithm and the CH nodes of each cluster are selected using ALO.

In [39], an enhanced flower pollination algorithm based on optimal EPO for fault diagnosis and network lifetime extension is proposed. In [40], an energy efficient opportunistic routing scheme with the EPO Q-learning (EPO-Q) approach is proposed for underwater wireless sensor networks. In [41], a hybrid EPO is developed to solve the load balancing, security enhancement, and energy consumption reduction problems. This hybrid EPO is combined with atomic search optimization (ASO) algorithm and used to improve the update function of EPO algorithm. In [42], a layered WSN architecture for dynamic clustering-based routing and coverage hole detection and recovery is proposed. Clusters are formed with K-means algorithm, while CH nodes are elected by determined weights (DW) and the best multi-hop route is constructed by multi-objective EPO algorithm (MO-EPO). Deepak et al. [43] proposed a grid-based clustering scheme, which selects CH nodes with FAHP-TOPSIS using three large-scale parameters such as energy, QoS, and distance, each with six sub-criteria as multi-criteria. After CH selection, the EPO is used for route establishment. In [44], a routing scheme using a kind of hybrid meta-heuristic optimization approaches combining whale optimization and lion optimization is proposed. This approach replaces the exploitation stage of whale optimization with a modified lion operator to prevent the solution from falling into local optimization early. It also improves the convergence rate and maintains the harmonic balance between exploitation and exploration that affects the stability of the route. In [45], a multi-objective based clustering and sailfish optimizer (SFO) guided routing scheme is proposed to achieve energy efficiency goals in WSNs. In this scheme, CH nodes are selected based on the fitness function formulated as a multi-objective and the SFO is used to select the optimal path to BS.

In clustering and routing schemes using various meta-heuristic optimization algorithms considered above, the fitness function is defined using the weights assigned by subjective desire not only without introducing fuzzy numbers when assigning weights to the various criteria, but also without applying any MCDM approach. So, it calculates a very imprecise fitness value for each sensor node, thus doing not actually lead to the optimal performance of meta-heuristic optimization algorithms.

Among the various MCDM approaches, FNCP is a MCDM approach using fuzzy pairwise interval scale [46]. FCNP, an ideal alternative to FAHP, can provide very reliable decision support compared to FAHP. On the other hand, VWA is a approach to adapt previously assigned weights based on state variable weight vectors [47]. Hence, in wireless rechargeable sensor networks (WRSNs), on-demand charging scheduling schemes to determine charging priority of charging request nodes by integrating several MCDM approaches or Q-learning with FCNP-VWA which assigns weights to multi-criteria have been developed by the authors, but no research results have been reported on improving its optimization performance by combining a meta-heuristic optimization algorithm with FCNP-VWA. In this paper, we propose a routing scheme that performs clustering using a hybrid FCNP-VWA and ALO integrated with the AFCM algorithm.

System model

Network model

The WSN consists of sensor nodes deployed in a two-dimensional plane and a fixed BS. Each node has a battery of

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finite capacity with limited power. Some of the assumptions needed to develop our protocol are as follows.

1) The network is consisted of N static sensor nodes and one BS that cannot move after it is deployed in the rectangular area of L×L.

Sensor nodes have the same limited battery capacity and the initial energy is equal to E_i^{ini}.

All sensor nodes have unique ID and know their locations.

All nodes have the ability to adjust the transmission power according to the distance.

Energy consumption model

There are the various energy consumption models and we adopt the "first-order radio model" in this study. In this model, the energy consumed to transmit the bit data is represented as follows.

$$E_{Tx}(l,d)=\begin{cases} l\times E_{elec}+l\times\varepsilon_{fs}\times d^2 & d<d_0 \\ l\times E_{elec}+l\times\varepsilon_{mpf}\times d^4 & d\geq d_0 \end{cases} \tag{1}$$

where E_{elec} is the energy consumed to transmit 1 bit data of the coded modulation, ε_{fs} and ε_{mpf} are the propagation loss coefficients, and d denotes the transmission distance. In Eq. (1), the power of d is determined by the transmission distance and the predefined threshold distance $d_0=\sqrt{\varepsilon_f s/\varepsilon_{mpf}}$ =87.7m. The energy consumed to receive the l bit data is expressed as follows.

$$E_{Rx}(l)=l\times E_{elec} \tag{2}$$

The energy consumed to sense the data during time t is depended on the sensing radius r.

$$E_{sen}(r,t)=kr^2\times t \tag{3}$$

where k is a constant coefficient and k^2 is an energy consumption rate. In this study, we do not consider energy for sensing the data since it is significantly small than energy for transmitting and receiving the data. In this study, relay nodes do not aggregate incoming packets, and only CH nodes consume energy E_{DA} for data aggregation. Thus, for a CH node that performs sensing, the total energy consumption is expressed as follows.

$$E_{total}=E_{Tx}(l,d)+E_{Rx}(l)+E_{DA}+E_{sen}(r,t) \tag{4}$$

Proposed protocol

The proposed routing protocol of centralized control mode by BS operates in two phases: clustering phase and data transmission phase. In the clustering phase, the whole network is first divided into k load balancing clusters using the AFCM algorithm. Then, for each cluster, a hybrid FCNP-VWA and ALO is applied to select CH nodes. In other words, the primary weights are assigned to six multi-criteria by FCNP and then compensated by VWA to make more accurate weights. Continuously, CH nodes are selected with the improved ALO using a new multi-criteria based fitness function defined based on these compensated weights. In the data transmission phase, the data sensed in the whole network area is transmitted to the BS through the CH nodes in a single hop mode.

Partitioning the whole network into clusters

The purpose of load balancing clustering is to partition the network into clusters, i.e. k *(k≦n)* sub-domains, so that the data traffic load sensed by sensor nodes in the network is equally distributed to the CH nodes of each cluster. Of several partitioning approaches, the AFCM [48] algorithm is adopted in this paper.

Different from the original FCM algorithm [49] which predetermines the number of clusters, the AFCM algorithm [48] does not decide k value in advance. The node placed at the rough center within the whole network is regarded as the Centralized Processing Node (CPN). CPN chooses the initiation nodes (INs) for k sub-domains or clusters based on their vicinity to itself. Each IN includes the nodes in a vicinity range of 5 units from the CPN into its own cluster. Here, the distance threshold of 5 units can be set arbitrarily, considering the practical applications. For k cluster set, the cluster allocation of the residual nodes is performed as follows.

The membership value u_{ij} is calculated using Eq. (5), in which it denotes the degree that node i belongs to cluster j.

$$u_{ij}=\frac{(\|x_i-c_j\|)^{\frac{-2}{m-1}}}{\sum_{l=1}^{k}(\|x_i-c_l\|)^{\frac{-2}{m-1}}},\ i=1,\cdots,n\quad j=1,\cdots,k \tag{5}$$

where u_{ij} is the center of mass of cluster j and m is the fuzzifier that determines the level of cluster vagueness. Due to lack of experimental or domain knowledge, m is generally set to 2 [50].

After obtaining the membership values, the sum of u_{ij} is calculated accordingly. When the node x_i has the same membership value for more than two clusters, the node is allocated to cluster with the lowest sum value of u_{ij}. This partitioning approach preliminarily calculates the sum of membership values of every node related to all the centroids i.e. INs. In addition, this approach is executed in a hierarchical way till all the nodes are related to any clusters.

Clustering phase

Multi-criteria or multiple objectives

We discriminate any node i in the network by the following six criteria: Residual energy (E_i^{res}), energy consumption rate (ECR_i), distance to BS ($D_{i,B}$), node neighboring degree (NND_i), average distance to neighboring nodes ($D_{i,nei}^{aver}$), signal-to-noise ratio of links (SNR_i). These criteria also become multiple objectives for selecting the optimal CH nodes.

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Residual energy (ECR_i): Once deployed within the network, sensor nodes get to know their residual energy by monitoring. This criterion is one of the most important criteria discriminating the energy status of each sensor node.

Energy consumption rate (ECR_i): This criterion, which represents the residual energy change over a certain time period, is also an important one that reflects the energy consumption status of each node. Due to the disproportionate traffic load of each node, the energy consumption rate varies with time, so it should be possible to measure this criterion's value in a real-time way. In this paper, the energy consumption rate for each node is calculated according to [51].

Distance to BS ($D_{i,B}$): This is the Euclidean distance between nodes *i* and BS calculated by the following equation:

$$D_{i,BS} = \sqrt{(x_i - x_{BS})^2 + (y_i - y_{BS})^2} \tag{6}$$

Node Neighborhood degree (NND_i): The node neighboring degree is a criterion of identifying the number of neighbors within the communication radius of node i, which is expressed as follows:

$$NND_i = \frac{n_{\max} - n_i}{n_{\max}} \tag{7}$$

where n_i is the number of neighbors within the communication radius of node *i*, and $D^{aver}_{i,nei}$ is the number of neighbors within the communication radius at any nodes in the network.

Average distance neighboring nodes ($D^{aver}_{i,nei}$): This is the average value of the distance to all neighbors within the communication radius of node *i*. The smaller $D^{aver}_{i,nei}$, the smaller power consumed in communication between nodes.

$$D^{aver}_{i,nei} = \frac{\sum_{j=1}^{n_i} D_{i,j}}{n_i}, \ (i \neq j) \tag{8}$$

where n_i represents the number of neighbors within the communication radius of node *i*, and SNR_i is the distance between node *i* and its neighbor *j*.

The signal-to-noise ratio of the link (SNR_i):The signal-to-noise ratio of the link, SNR_i is calculated by the following expression.

$$SNR_i = 10\log_{10}\left(\frac{P_i^{signal}}{P_i^{noise}}\right) \tag{9}$$

where P_i^{signal} and P_i^{noise} denote the effective signal power and the effective noise power of node *i*, respectively.

Allocating weights to multi-criteria

FCNP is a approach to assign weights to multi-criteria using fuzzy numbers such as triangular fuzzy numbers on fuzzy pairwise interval scales. An overview of weighting multi-criteria by FCNP is described in [23], [24]. VWA is a weight compensation approach that automatically emphasizes or weakens the weights assigned by FCNP according to their importance degree using a state-variable weight vector. A review of VWA refers to [25].

The pairwise opposite matrix for the relative weight determination of six multi-criteria considered in **section 4.2.1** is shown in **Table 1**.

Table 1: The fuzzy pairwise opposite matrix

Evaluation criteria	E_i^{res}	ECR_i	NND_i	NND_i	$D^{aver}_{i,nei}$	SNR_i
E_i^{res}	0	3^+	0	5^+	5^+	6^+
ECR_i	3^-	0	3^-	2^+	2^+	3^+
$D_{i,B}$	0	3^+	0	5^+	5^+	6^+
$NND_i^{\deg}$	5^-	2^-	5^-	0	0	2^+
$D^{aver}_{i,nei}$	5-	2^-	5^-	0	0	2^+
SNR_i	6-	3^-	6^-	2^-	2^-	0

Table 2. Weight of evaluation criteria

Evaluation criteria	Weight ($w_i^{'}$)	Compensated weight (w_i)
E_i^{res}	0.2130	0.2158
ECR_i	0.1667	0.1539
$D_{i,B}$	0.2130	0.2328
$NND_i^{\deg}$	0.1420	0.1511
$D^{aver}_{i,nei}$	0.1420	0.1151
SNR_i	0.1233	0.1313

Table 2: shows the normalized weights assigned to each of the resulting evaluation criteria using FCNP and the weights compensated using VWA.

The multi-criteria based fitness function

The main goal of the clustering phase is to choose the optimal CH node for each cluster constructed by the AFCM during each round. This is realized by blending the multi-criteria or multiple objectives discriminating each node. Most of the fitness functions for the meta-heuristics are defined by allocating the equal weights to these criteria or objectives. In fact, every weight value must be determined based on the importance or priority of each criterion or each objective among the overall fitness function. These weights' values play a decisive role in determining the influence degree of the corresponding criterion or objective function among the overall fitness function.

In this paper, we use the weights of six multi-criteria assigned by FCNP and compensated by VWA, ($w_6, \ldots, w_6$). The fitness value of node *i* is calculated as follows:

$$FF_i = w_1 \frac{E_i^{res}}{E^{\max}} + w_2 \frac{ECR^{\max} - ECR_i}{ECR^{\max}} + w_3 \frac{D_{BS}^{\max} - D_{i,BS}}{D_{BS}^{\max}} + w_4 \frac{NND_i^{\deg}}{NND^{\deg\_\max}} + w_5 \frac{D^{aver\_\max} - D^{aver}_{i,nei}}{D^{aver\_\max}} + w_6 \frac{S}{SN} \tag{10}$$

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where, the *max* subscripts in E^{max}, E_i^{res}, etc. in Eq. (10), denote the maximum values of the corresponding criteria. Eq. (10) implies that the node *i* with higher E_i^{res}, lower $D_{i,B}$, shorter $D_{i,B}$, higher NND_i, shorter SNR_i, and higher SNR_i can get bigger fitness value.

Selecting CH nodes by the improved ALO

Step1: Initialize ALO parameters such as the number of search agents (antlion) and the number of iterations. Based on them, randomly set the antlions.

Step2: Calculate the fitness values of antlions using Eq. (10). Assume that the antlion with the largest value of the obtained fitness values is the elite antlion.

Step3: Select one antlion using Roulette wheel for each ant. Subsequently, update *c* and *d* to adaptively reduce the radius of the ant's random walk hyper-sphere using the following equations:

$$c_t = \frac{c_t}{I} \tag{11}$$

$$d_t = \frac{d_t}{I} \tag{12}$$

$$I = 10^w \frac{t}{T} \tag{13}$$

where *I* is the ratio, d_t the minimum value of all random walks in the t^{th} iteration, d_t the vector containing the maximum of all random walks in the t^{th} iteration, T the number of maximal iterations, and *w* the constant that controls the appropriate exploitation level.

Step4: Using the following Eq. (14) and Eq. (15), force each ant to walk randomly so that its position can be updated towards a randomly selected ant lion.

$$A(i) = [0; cumsum(2r(i_1)-1; cumsum(2r(i_2)-1; \cdots; cumsum(2r(i_{iter})-1] \tag{14}$$

$$r(\Delta) = \begin{cases} 1, & if \ \ rand > 0.5 \\ 0 & if \ \ rand \le 0.5 \end{cases} \tag{15}$$

where $A(i)$ is the random walk motion of ant *i*, *iter*-the number of iterations, and $r(\Delta)$-the random generating function when $A(i)$ is the step size of random walk.

Step5: After randomly moving each ant, the positions of the ants are normalized using the following equation, so that their positions do not escape from the search space.

$$A_t(i) = \frac{(A_t(i) - a(i)) \times (d(i) - c_t(i))}{d_t(i) - a(i)} + c(i) \tag{16}$$

here, $A_t(i)$ is the position of the i^{th} ant in the t^{th} iteration, $a(i)$ and $c(i)$-the minimum and maximum values of the random walk of the i^{th} ant, respectively, and $c_t(i)$ and $d_t(i)$-the minimum and maximum values of the random walk of the i^{th} ant in the t^{th} iteration.

Step6: Update the position of each ant using the following equation:

$$A_t(i) = \frac{AL_t + EL_t}{2} \tag{17}$$

here, $A_t(i)$ is the position of the i^{th} ant in the t^{th} iteration, AL_t-the random walk to the periphery of antlion selected by Roulette wheel in the t^{th} iteration, and E_t-the random walk to the periphery of the elite antlion in the t^{th} iteration.

Step7: For all ants, the fitness values at the updated locations are calculated using Eq. (10) and compared with that of its random elite antlion. If the fitness value of any ant is larger than that of its random elite antlion, the antlion is replaced with that ant. On the other hand, the fitness value of the chosen antlion is compared with that of the random elite antlion. It the former is larger than the latter, this antlion becomes a new elite antlion.

Step8: By repeatedly executing the process from step 3 to the number of maximal iterations, the finally obtained elite is selected as a reasonable alternative.

Algorithm 1 shows the pseudo code of the clustering phase considered above.

Algorithm 1. A centralized clustering using AFCM and a hybrid FCNP-VWA-ALO

Input: Set of alive sensor nodes, network size, number of search agents, maximum number of iterations

Output: Optimal CH nodes

1: Divide whole network into load-balancing clusters using AFCM;

2: Assign relative weights to six criteria with FCNP;

3: Compensate assigned weights by FCNP with VWA;

4: **for** each cluster in whole network

5: Initialize number of search agents and maximum number of iterations;

6: Select initial ants and antlions randomly;

7: Calculate the fitness values for ants and antlions using Eq.(10);

8: Set antlion with the highest fitness value as temporary elite;

9: **while** (current iteration<maximum number of iteration)

10:**for** each ant in cluster

11:Select an antlion using Roulette wheel;

12: Renew towards random chosen antlion and elite using Eq.(14) and Eq.(17);

13:Perform max-min normalization using Eq.(18) to fall random walks of ants into search space;

14: Renew position of ant using Eq.(17);

15: **end for**

16: Calculate the fitness values of all ants;

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17: Swap antlion for its corresponding ant if it has greater fitness value than antlion;

18: Renew elite for its corresponding antlion if any antlion has greater fitness value than elite;

19: **end while**

20: Regard elite antlion as CH node;

21: **return** CH node

22; **end for**

Data transmission phase

In this phase, the data sensed in the whole network area is transmitted to the BS in a single hop mode through the CH nodes of each cluster.

Performance evaluation

Simulation setup

The proposed routing scheme was tested on MATLAB 2020a. The performance of the proposed scheme called AFCM-FVA-CS is compared with existing schemes, LEACH [53] and two ALO-based clustering schemes such as ALOC [52] and K-LionER [38]. In the simulation experiment, 100 sensor nodes are randomly placed in 100×100 m2 area and BS is fixed at (0, 0). However, only in case of the simulation for successfully delivered packet rate (SDPR) metric, the number of sensor nodes is varied from 100 to 300 to evaluate the proposed and compared schemes. The size of the data packet and the control packet is 4000 bits and 200 bits, respectively. The other parameters are set as in Table 3.

The performance metrics used in the extensive simulations are as follows:

·**Network energy consumption (NEC)**: This is determined as the amount of energy consumed by all sensor nodes in the network. A smaller NEC means that the clustering scheme utilizes the given energy more effectively with varying the number of rounds.

Table 3. Simulation parameters

Parameters	Values
Network size	$100\times100\ m^2$
Number of nodes	100
Location of BS	(0, 0)
Initial energy	2J
Length of data packet	4000bit
Length of control packet	200bit
E_{elec}	50nJ/bit
ε_{fs}	$10pJ/bit/m^2$
ε_{mpf}	$0.0013pJ/bit/m^4$
E_{DA}	5nJ/bit/signal

·**Residual energy variation (REV)**: It is defined as the average of REVs of all nodes in the network. The already dead nodes are excluded from this calculation. A smaller REV represents that the clustering scheme utilizes the energy of all sensor nodes in the network in better-balanced way.

·**Successfully delivered packet rate (SDPR)**: This metric is defined as the ratio of the number of data packets successfully transferred to BS compared to the total number of the sensed data packets sent by CM nodes.

·**Network lifetime (NL)**: It is defined as the number of rounds till the first sensor node dies (FND), the one till the half of nodes in the network die (HND) and the one till the last node dies (FND).

Simulation results and analysis

Network energy consumption (NEC)

Figure 1 and **Table 4** show the simulation results of NEC according to varying the number of rounds. From these results, it can be seen that the proposed scheme consumes the smallest amount of energy. When the number of rounds is 600, the proposed scheme consumes 5.1mJ of energy. However, LEACH, ALOC and K-LionER schemes consume 11.7mJ, 6.9mJ and 6.2mJ of more energy, respectively.

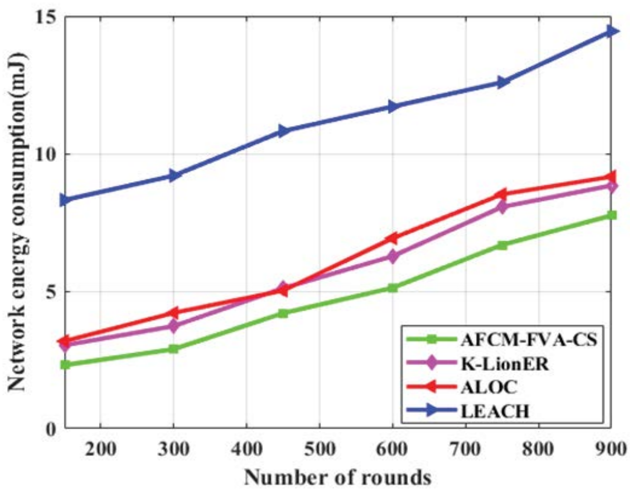

Fig. 1: Comparison of NEC with varying the number of rounds

Less energy consumption implies that the sensor nodes operating according to this scheme can have the stability period of bigger number of rounds. It is because of exploiting the AFCM and a hybrid FCNP-VWA-ALO, and obtaining the optimum energy consumption balance. K-LionER scheme comes the next of the proposed scheme, the third is ALOC scheme and the last is LEACH scheme. LEACH scheme shows the biggest energy consumption. It is because this scheme selects the CH nodes in a probabilistic way without considering multiple factors, thus consuming more energy.

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Table 4. Network energy consumption (mJ)

Number of rounds ⇨ Schemes ⇩	150	300	450	600	750	900
AFCM-FVA-CS	2.31	2.89	4.20	5.12	6.68	7.75
K-LionER	3.03	3.73	5.11	6.27	8.06	8.84
ALO	3.18	4.21	5.02	6.92	8.52	9.16
LEACH	8.31	9.20	10.82	11.71	12.59	14.45

Residual energy variation (REV)

REV metric indicates balance and fairness of energy consumption of each sensor node. A smaller REV reveals better balance and fairness of energy consumption. The simulation results with respect to REV with varying the number of rounds are shown in **Figure 2** and **Table 5**. From these results, we can see that the REV of proposed scheme is the smallest compared to other schemes. That is, the proposed scheme has the REV of 40.4%, 76.6% and 83.5% compared to LEACH, ALOC and K-LionER schemes, respectively.

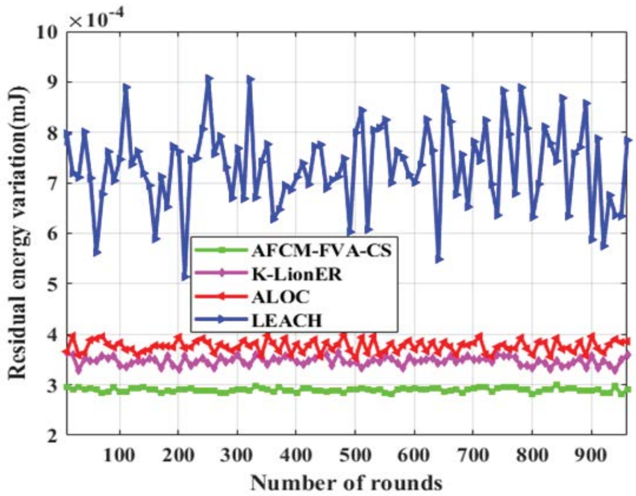

Figure 2: Comparison of REV with varying number of rounds

The reasons are as follows: First, the proposed scheme uses the AFCM to realize the load-balancing clustering. Next, for such divided clusters, the proposed scheme assigns weights to multi-criteria by FCNP-VWA and selects CH nodes with the improved ALO based on these weights. At this time, the fitness values of sensor nodes are calculated to exploit these comparative accurate weights assigned to six multi-criteria. Thus, this scheme expends the energy of each node more evenly. Ascending order in terms of REV of three compared schemes is as follows: K-LionER, ALOC and LEACH schemes. That is, K-LionER scheme follows the proposed scheme. This is due to it divides the whole network into several clusters using K-means approach. K-LionER and ALOC schemes use the equal weights to multi-criteria to choose CH nodes. Thus, the impact of multiple factors or multi-criteria which influence CH nodes selection is not taken into consideration exactly. LEACH scheme shows the biggest REV. It is because this scheme selects CH nodes randomly. Furthermore, during clustering, any factor or criterion such as residual energy is not wholly taken into consideration.

Table 5: Improvement ratio of REV over compared schemes

Schemes	Improved ratio (%)
K-LionER	83.50
ALO	76.55
LEACH	40.36

Successfully delivered packet rate (SDPR)

In this simulation, we place sensor nodes from 100 to 300 within 100×100 m^2 area randomly. That is, the simulation is conducted by the number of nodes, not the number of rounds under the fixed number of sensor nodes.

Figure 3 and **Table 6** show the simulation results of SDPR with varying the number of nodes. From these simulation results, it can be seen that SDPR of the proposed scheme is the highest. The proposed scheme uses a criterion of energy consumption rate (ECR) except the criteria used in K-LionER and ALOC schemes. Thus, the status change of the sensor nodes due to the unforeseen accidents is taken into account in selecting CH nodes.

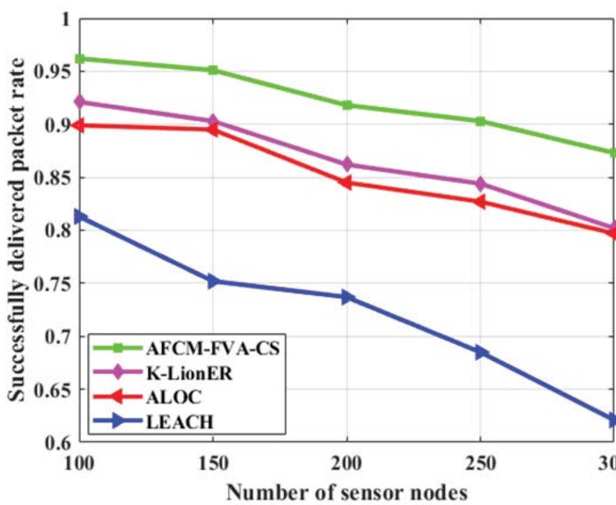

Figure 3: Comparison of SDPR with varying number of nodes

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Table 6: Successfully delivered packet ratio

Number of nodes ⇨ Schemes ⇩	100	150	200	250	300
AFCM-FVA-CS	0.962	0.951	0.918	0.903	0.873
K-LionER	0.921	0.903	0.862	0.844	0.802
ALO	0.899	0.895	0.845	0.827	0.797
LEACH	0.813	0.752	0.737	0.685	0.621

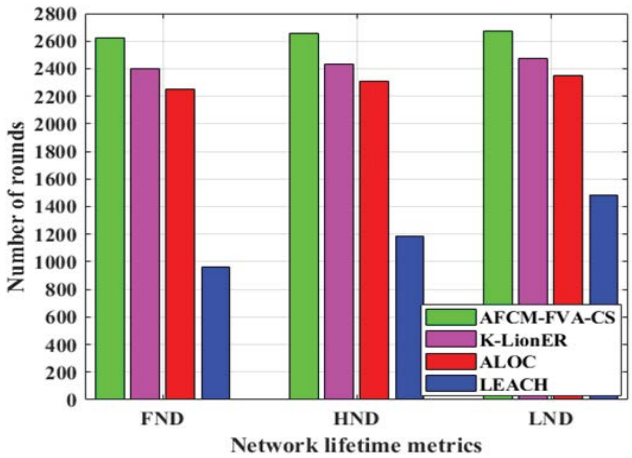

Figure 4: Comparison of NL with varying number of rounds

In other words, the sensor node with lower ECR has higher possibility which is chosen to CH node. Thus, the proposed scheme increases the SDPR of the sensed data packet. Ranking three compared schemes in terms of SDPR, K-LionER comes the next of the proposed and LEACH shows the lowest SDPR. The difference between K-LionER and ALOC schemes in terms of this criterion is not so big. LEACH scheme randomly chooses CH nodes without considering any factor, thus having the lowest SDPR.

Network lifetime (NL)

Figure 4 and **Table 7** show the simulation results of NL. The proposed scheme has the longest NL. NLs of the proposed scheme in terms of FND, HND and LND are xx, xx and xx rounds, respectively. NL of the proposed scheme related to FND is increased by 272.9%, 116.6% and 109.2% compared to LEACH, ALOC and K-LionER schemes, respectively. Since the proposed scheme has the smallest REV, it is not without reason that it has the longest NL. K-LionER comes the next and outperforms the other compared schemes. This implies that when K-means approach is applied to clustering, it predominates over the schemes like ALOC which don't use a such approach. LEACH scheme has the lowest NL.

Figure 5 and **Table 8** show the simulation results in terms of the number of alive nodes with varying the number of rounds. It can be seen that the proposed scheme makes much more sensor nodes alive. The numbers of rounds till there are no longer any active node are 1486, 2352, 2473, and 2668 for LEACH, ALOC, K-LionER and AFCM-FVA-CS schemes, respectively.

In the long run, it can be seen that the proposed scheme outperforms other existing schemes with respect to the above four metrics.

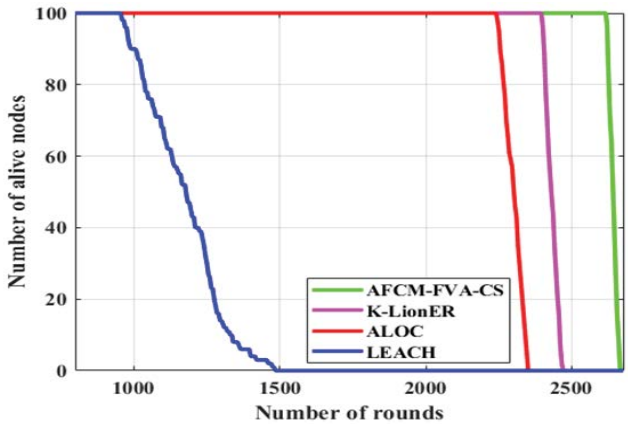

Figure 5: Comparison of the number of alive nodes in terms of number of rounds

Table 7: Improvement ratio of NL over compared schemes

NL metrics ⇨ Schemes ⇩	FND	HND	LND
K-LionER (%)	109.2	108.9	107.9
ALO (%)	116.6	114.8	113.4
LEACH (%)	272.9	223.5	179.5

Table 8: Number of alive nodes (rounds)

Number of alive nodes ⇨ Schemes ⇩	80	60	40	20	0
AFCM-FVA-CS	2627	2638	2646	2653	2668
K-LionER	2410	2422	2438	2452	2473
ALO	2268	2288	2313	2331	2352
LEACH	1037	1130	1211	1276	1486

Conclusion

The lifetime of the energy-constrained WSNs is significantly improved by exploiting the intelligent

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optimization approaches. In this paper, we have proposed a novel clustering scheme using the AFCM and a hybrid FCNP-VWA-ALO. This scheme uses the AFCM algorithm to partition the networks into the several disjoint clusters. In addition, it optimally chooses the CH nodes for the partitioned clusters by using an improved ALO based on a new multi-criteria based fitness function. The maximum network lifetime which is the ultimate goal of this work can be achieved by the proposed scheme. This clustering scheme has a superior performance over clustering schemes using ALO alone. The proposed scheme decreases REVs by 40.4%, 76.6% and 83.5% than LEACH, ALOC and K-LionER schemes, respectively. As a result, it extends the network lifetime by 272.9%, 116.6% and 109.2% than LEACH, ALOC and K-LionER schemes in terms of FND, respectively. In future, the design idea of integrating MCDM with meta-heuristic algorithms will be extended toward constructing the routes to BS and multi-criteria itinerary planning for mobile sink (MS) in WSNs with multiple MSs.

Declarations

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Conflict of interest

The authors declare no conflict of interest.

Availability of data and materials

The data used to support the findings of this study are available from the corresponding author upon request.

Code availability

The code used to support the findings of this study are available from the corresponding author upon request.

Authors' contributions

Man Gun Ri researched the literature, conceived the study concepts, and designed the protocol. Ye Hyang Choe carried out the simulation and analyzed the simulation results. Se Hun Pak revised the manuscript.

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