Computer Science and Information Technologies
Vol. 7, No. 1, March 2026, pp. 74~82
ISSN: 2722-3221, DOI: 10.11591/csit.v7i1.p74-82

An uneven cluster-based routing protocol for WSNs using a hybrid MCDM and max-min ant colony optimization

Man Gun Ri[1], Pyong Gwang Kim[2], Jin Sim Kim[3]
[1]Faculty of Communication, Kim Chaek University of Technology, Pyongyang, Democratic People's Republic of Korea
[2]Faculty of Artificial Intelligence, Pyongyang University of Computer Technology, Pyongyang, Democratic People's Republic of Korea
[3]International Technology Corporation Center, Kim Chaek University of Technology, Pyongyang, Democratic People's Republic of Korea

Article Info

Article history:

Received Jul 23, 2025
Revised Dec 9, 2025
Accepted Jan 1, 2026

Keywords:

Cluster-route fixation
Hybrid FCNP-VWA-TOPSIS
Improved max-min ACO
Routing tree formation
Wireless sensor network

ABSTRACT

In energy-constrained wireless sensor networks (WSNs) composed of sensor nodes (SNs) characterized by multi-criteria contradictory with each other, it is still one of the challenges to be solved to figure out how to combine multi-criteria with each other and how to use an intelligent optimization (IO) algorithm for developing an optimal cluster-based routing protocol. In this article, we overture a new routing protocol based on uneven cluster using the hybrid FCNP-VWA-TOPSIS (FVT) and an improved max-min ant colony optimization (ACO). This scheme uses the hybrid FVT to perform the clustering, and uses an improved max-min ACO to configure a routing tree for the relay transmission of sensed data. The extensive simulation experiments have been carried out to show that the proposed scheme greatly prolongs the network lifetime (NL) by achieving an energy consumption balance superior to the previous schemes.

Corresponding Author:

Jin Sim Kim
International Technology Corporation Center, Kim Chaek University of Technology
60 Kyogu, Sungri Street, Pyongyang, Democratic People's Republic of Korea
Email: kjs8921@star-co.net.kp

1. INTRODUCTION

Among the various routing protocols of wireless sensor networks (WSNs), the most attractive one is the routing protocol based on clustering for its energy efficient utilization [1]. In general, cluster-based routing protocols play a role in establishing and maintaining an energy-efficient route for reliable and efficient communication. In WSNs, sensor nodes (SNs) are characterized by multi-criteria which are conflicting each other. Multi-criteria clustering algorithms specify the cluster head (CH) node set for data aggregation and relay transmission. Considering this feature of WSNs, there has been a great deal of study on the application of intelligent optimization (IO) approaches, including multi-criteria decision making (MCDM) or fuzzy logic (FL) for clustering routing. There are many different approaches, such as a FL-based [2], using tutorial MCDM methods like analytic hierarchy process (AHP) [3], technique for order preference by similarity to ideal solution (TOPSIS) [4], and preference ranking organization method for enrichment evaluation (PROMETHEE) [5] and combining a few IO algorithms, for example, ant colony optimization (ACO) and FL [6]. The objective of the clustering routing optimization is to maximally extend the network lifespan by keeping the balance of the energy consumption of every SN by combinatorial consideration of multiple criteria throughout the entire process of the cluster-based routing, while ensuring network stability, reliability and connectivity.

However, so far, the hybrid MCDM method and meta-heuristic IO algorithms have not been well combined to achieve the balance of energy consumption during the cluster-route fixation stage. Ri and Kim [7] suggested a scheme to optimize the balance of energy consumption by using the hybrid FCNP-VWA-

ELECTRE throughout the cluster-route fixation stage in the routing protocol based on the uneven cluster. However, this method only performs uneven clustering and selects the next hop CH node using the integrated FCNP-VWA-ELECTRE, so there is no guarantee that the route to BS is optimal. Meanwhile, the authors in [6] proposed a scheme to constitute the routing tree through proceeding the unequal clustering by FL and choosing the proper next relay CH node with max-min ACO. The FL method is not superior to the MCDM method in combinatorial optimization of various criteria, and furthermore, the estimation of paths pioneered by ants in the max-min ACO is done using only distance and residual energy (RE), thus leaving the margin for more rational evaluation. This motivates us to propose a novel routing protocol which uses a hybrid FCNP-VWA-TOPSIS (FVT) and an improved max-min ACO to chose the optimal CH nodes and construct the optimal routing tree from selected CH nodes to the BS.

The ultimate goal of this study is to open up a novel uneven clustering routing protocol which can extend the network lifespan maximally by using a hybrid MCDM method and improved max-min ACO during the cluster-route fixation stage for WSNs to utilize the limited energy of all SNs in a maximally efficient and balanced way. Up to the authors' knowledge, this study is the first to adopt the hybrid FCNP-VWA-TOPSIS, the best of the hybrid MCDM method and the improved max-min ACO during the cluster-route fixation stage of the unequal clustering routing protocol. The key contributions of our study are as follows:

i) Using the exact weights assigned to the multiple criteria with FCNP-VWA, we overture the clustering scheme based on the hybrid FVT which chooses the best CH node, enlisting CM nodes in the most suitable CH node by TOPSIS, so optimally balancing the energy expenditure.
ii) We propose a routing tree formation scheme ensuring the balance of the energy expenditure optimally during the data gathering stage by selecting the most suitable route for relaying the data with the improved max-min ACO which uses the multi-criteria' weights allocated with FCNP-VWA.
iii) The extended simulative experiments have revealed that the suggested routing scheme has far superior performance to the other existing schemes.

The remainder of our article is constructed as follows: the related works are debated in section 2. In section 3, the network and the energy consumption models are delineated and the proposed scheme is delineated in section 4. The extended simulation results and their analysis are displayed in section 5, and section 6 concludes this work.

2. RELATED WORKS

We briefly summarize the previous related works in terms of routing protocols based on MCDM or IO methods among several clustering routing protocols. In [2], a clustering scheme which selects the optimal CHs by FL which uses several criteria is proposed. A clustering scheme which selects the CH node with TOPSIS using multi-criteria proposes by Sen *et al.* in [4]. Rajpoot and Dwivedi [5] propose a clustering method which uses tutorial MCDM including TOPSIS, AHP and PROMETHEE. In [8], a scheme to select a CH node with MCDM method called ELECTR-I using several criteria is suggested.

A method for constructing the routing tree by conducting the unequal clustering by FL which uses 3 multiple criteria and by selecting the suitable next relay CH node with the max-min ACO is suggested [6]. Mehta and Saxena [9] proposed a grid-based clustering method, which uses three broad parameters to select the CH node by fuzzy analytic hierarchical analysis (FAHP)-TOPSIS. After CH selection, this scheme used the emperor penguin optimization (EPO) for route fixation. Literature [10] proposed a method which chooses the optimum CH adopting the generalized intuitionistic fuzzy soft set approach, constructing the routing tree with shark smell optimization and genetic algorithm (GA). Gamal *et al.* [11] proposed a FL LEACH-based particle swarm optimization (PSO) scheme, which utilizes hybrid PSO and a K-means clustering to form cluster, and selects the primary CH and secondary CH nodes using FL. In [12], a routing method based on EPO and Q-learning method was suggested for underwater WSN. A hybrid EPO method was proposed to deal with 3 issues: load balance, security enhancement, and reducing the energy expenditure [13]. In [14], the WSN architecture which consists of 4 stages was suggested. It is clear that the routing methods mentioned above adopts either individual MCDMs or the hybrid FAHP-TOPSIS for CH selection or enlisting CMs to CH for clustering, and use IO schemes for the selection of next relay CH for construction of the routing tree.

Singh *et al.* [15] is proposed a CH node selection method that applies a hybrid GA using mutation operator based on greedy strategy for IoT enabled heterogeneous WSNs. Chaurasia and Kumar [16] suggested a new method based on the adaptive meta-heuristic based clustering and routing algorithm for IoT-assisted WSN (ACRA) to address the issues of deadlock and livelock in IoT assisted WSN. Abraham and Vadivel [17] proposed a clustering routing scheme, which employs the flamingo search algorithm (FSA) to proceeds CH node selection and uses Q-learning to select the routes from CHs to BS. In [18], the sea horse optimizer (SHO) is blended with the opposition-based learning (OBL) and the greedy selection (GS) strategies to be used in selecting CH nodes. Tang and Nie [19] exploited the swarm intelligence approach to blend with the features of WSN, and suggested a clustering scheme that uses the chaos PSO to choose the CH nodes.

Chaurasia *et al*. [20] proposed a clustering routing protocol called EEM-CRP, which employs dragonfly algorithm to choose the optimal CH nodes and the routes from the selected CHs to BS. In [21], in order to choose the optimal CH nodes, authors propose a hybrid algorithm called fire fly replaced position update in dragonfly. Wang *et al.* [22] suggest an enhanced pelican optimization algorithm (POA) which blends the Levy flight with the original POA to improve the CH node selection performance. Prasad *et al.* [23] employ multi-objective optimization using ratio analysis to choose the CH nodes, and use the minimum spanning tree formation method based on modified Dijkstra to decrease intra-cluster communication distance and to partition the workload on CM nodes evenly. Barnwal *et al.* [24] uses whale moth flame optimization meta-heuristic algorithm to choose the CH nodes and exploits improved African buffalo optimization (IABO) to form the routes from CH nodes to BS. In this article, we overture an unequal clustering routing protocol. The protocol adopts the hybrid FVT to choose a CH node and to enlist CMs to a CH. It also adopts an improved max-min ACO which uses the multi-criteria' weights allocated with FCNP-VWA to establish the route to BS.

3. SYSTEM MODEL

3.1. Network model

The assumptions for the considering WSN are as below:

i) The considering network has N stationary SNs randomly located in a rectangular domain and a fixed BS that is not energy-limited and a long way off a surveillance region.
ii) All SNs have a battery with the limited capacitance which is not able to recharge and a unique ID. These nodes are heterogeneous and don't know the information of their locations.
iii) SNs can control their transmission power in accordance with the distance from the receiver to themselves.

3.2. Energy expenditure model

We use the "first-order radio model" for the energy expenditure model. The energy spent for transmitting the k-bit data is estimated as in (1).

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

Here, $\varepsilon_{fs}$and $\varepsilon_{mpf}$are coefficients of the propagation loss, $E_{elec}$is the energy spent for transmitting 1-bit data, while d is the transmission distance. The power of d is specified by d and the threshold distance $d_0=\sqrt{\varepsilon_{fs}S/\varepsilon_{mpf}}$=87.7 m. The energy consumed for the data reception of k bits is calculated as in (2).

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

It is assumed that the relay nodes don't accumulate the input packets. Only CHs gather the sensed data. Therefore, the total energy expenditure of a CH node, if the energy spent for gathering data is denoted EDA, is expressed as in (3).

$$E_{total}=E_{Tx}(k,d)+E_{Rx}(k)+E_{DA} \tag{3}$$

4. PROPOSED PROTOCOL

The proposed protocol operates by dividing the cluster-route fixation stage and the data gathering stage. The cluster-route fixation stage includes the clustering step for the selection of CHs and enlists CMs to the proper CHs, and the routing tree formation step to select the next relay CH for every CH and set the route to BS. The hybrid FVT and the improved max-min ACO are used in the clustering step and the routing tree construction step. In the data gathering stage, the data sensed in the entire network area is sent to BS via the routing tree.

4.1. Cluster-route fixation

4.1.1. Assigning weights to multi-criteria

The weight assignment method by FCNP-VWA is according to [25] proposed by the authors. To characterize node i, we use six multiple criteria like RE, distance to BS (Dis), energy consumption ratio (ECR), node neighbor degree (NND), signal to noise ratio of the link (SNR), and node location importance degree (NLID). The NLID of each node is predetermined for each node by the method of [26]. Table 1 shows the fuzzy pairwise comparison matrix (FPCM) for the determination of relative weights of these multiple criteria. The consistency check result for the constructed FPCM is $AI=0.861$, that is $0<AI\leq 0.1$, thus it satisfies the consistency. Table 2 shows the normalized weights (w_i') allocated to every criterion with FCNP-VWA.

Table 1. The fuzzy pairwise comparison matrix between criteria

Criteria	RE	Dis	ECR	NND	SNR	NLID
RE	0	0	4^+	6^+	7^+	5^+
Dis	0	0	4^+	5^+	7^+	5^+
ECR	4^-	4^-	0	4^+	5^+	3^+
NND	6^-	5^-	4^-	0	3^+	3^-
SNR	7^-	7^-	5^-	3^-	0	4^-
NLID	5^-	5^-	3^-	3^+	4^+	0

Table 2. Compensated criteria weight

Criteria	Weight (w_i)	Compensated weight (w_i)
RE	0.2222	0.2255
Dis	0.2191	0.2339
ECR	0.1759	0.1736
NND	0.1296	0.0846
SNR	0.1019	0.1132
NLID	0.1513	0.1692

4.1.2. Cluster construction

BS begins clustering by broadcasting BS_start_Msg ($w_1,\ldots, w_6$, $d_{i,j}^{max}$, $d_{i,j}^{min}$) within the entire network to inform all SNs the multiple criteria' weights. All SNs in the network receive this message and grasp the Dis based on the received signal strength. At the start of every round, all SNs broadcast Hello_Msg (i, E_i^{res} , $d_{i,BS}$, ECR_i , $NLID_i$, R_i^{compe}) to exchange their local information for CH node selection. In this message, i denotes the node i's ID, E_i^{res}-the RE of node i, $d_{i,BS}$- the distance from node i to BS, ECR_i- the energy expenditure rate of node i, $NLID_i$- node i's position importance degree and R_i^{compe}-node i's competition radius [1]. The radius of the competition of node i- R_i^{compe} is calculated as in (4).

$$R_i^{compe} = (1 - \gamma \times \frac{d_{i,j}^{max} - d_{i,BS}}{d_{i,j}^{max} - d_{i,j}^{min}}) \times R_i^{max} \tag{4}$$

Here, γ is a constant coefficient, taking the value of interval [0, 1], and R_{max} is the longest competitive radius which is predefined.

After the reciprocation of Hello_Msg(•), the SNs are known the neighbor degree of node i and SNR_i. As soon as the reciprocation of the local information of nodes is finished, every node begins the CH competition. For doing this, at first, a decision matrix that is going to be used for TOPSIS is formed. Table 3 shows the example of 6 criteria' values for 6 SNs involving itself if a SN receives Hello_Msg(•) from 5 neighbor nodes. After that, the upper bound and the lower bound of the solutions are computed.

Table 3. Criteria values of sensor nodes

Criteria	RE	Dis	ECR	NND	SNR	NLID
RE	0.23	17.1	0.003	1.22	0.012	1
Dis	0.16	25.3	0.005	1.45	0.082	3
ECR	0.42	72.7	0.009	1.84	0.054	2
NND	0.31	33.2	0.004	1.42	0.073	0
SNR	0.27	45.7	0.006	1.68	0.024	1
NLID	0.11	78.1	0.008	1.83	0.016	3

The separations (d_i^* and d_i^0) from the upper bound and the lower bound are computed, then for each SN, the relative closeness to the upper bound is obtained and the final priority is determined using the relative closeness (C_i^*) as shown in Table 4. In such a way, all SNs compute C_i^* which represents the preference for themselves and neighbor SNs. When neighbor nodes with larger C_i^* compared to its is in existence, it gives up CH emulation and becomes CM. When it has the largest C_i^*, it broadcasts CH_Msg(·) in the competitive radius R_i^{compe} and inform its CH election.

The SNs which received CH_Msg(·) reply to it by sending Join_Msg(·). If the nodes receive more than 2 CH_Msg(·), they join in the most proper CH with FVT as in CH selection. Such a CH has the largest closeness value to the positive ideal solution C_i^*. The node which doesn't receive even a single CH_Msg(·) for a certain period makes a declaration itself as the CH.

Table 4. Priorities of sensor nodes

Sensor node	d_i^*	d_i^0	C_i^*	Preference
SN1	0.5969	0.8813	0.5962	1
SN2	0.6160	0.8503	0.5799	2
SN3	0.8078	0.7791	0.4910	3
SN4	0.5583	0.8150	0.5934	4
SN5	0.6611	0.5717	0.4638	5
SN6	0.0766	0.4666	0.3024	6

4.1.3. Constructing a routing tree

To construct a routing tree, CH nodes broadcast Next_Hop_CH_Msg (i, E_i^{res}, $d_{i,BS}$, ECR_i, n_i^{deg}, SNR_i, $NLID_i$) within rR_i^{compe}, here r is the smallest integer which allows any CH to include at least one neighbor CH in accordance with [1]. n_i^{deg} is the neighboring degree of node *i*. After broadcasting NextHop_CH_Msg(•), all CHs grasp forward neighbor CHs whose Dis is shorter than one of itself. Then the improved max-min ACO shown below determines the next hop CH node. At the beginning of the route establishment, each ant is placed at CH nodes within the network and then randomly chooses the CH nodes to visit. First, the probability that an ant *k* placed at CH node *i* chooses CH node *j* is calculated. Then the visibility value is calculated with the criteria' weights which are assigned by FCNP-VWA as in (5):

$$\eta_{i,j} = w_1 E_j^{res} + w_2 \frac{1}{d_{j,BS}} + w_3 \frac{1}{ECR_j} \tag{5}$$

In the above equation, w_1, w_2 and w_3 are the weights of the criteria such as RE, Dis and ECR allocated by the FCNP-VWA, while E_j^{res}, $d_{j,BS}$ and ECR_j are the normalized criteria' values of RE, Dis and ECR of CH node *j*, respectively. Next, when the ants starting from each CH node arrive at the BS, we use the evaluation function of (6) to select m solutions, i.e., routes with the largest evaluation function value in the current iteration. Then, EF_{route}^k, the value of evaluation function for the route with *s* hops which ant *k* follows, is calculated as in (6) to (8):

$$EF_{route}^k = \kappa \frac{1}{FC_{route}^k} + \delta \frac{1}{V_{route}^k} \tag{6}$$

$$FC_{route}^k = \sum_{i=1}^{s} C_i = \sum_{i=1}^{s} (w_1 E_j^{res} + w_2 \frac{1}{d_{j,BS}} + w_3 \frac{1}{ECR_j} + w_4 \frac{1}{n_i^{deg}} + w_5 SNR_i + w_6 \frac{1}{NLID_i}) \tag{7}$$

$$V_{route}^k = \sqrt{\frac{1}{s}\sum_{i=1}^{s} (C_i - \frac{1}{s}\sum_{i=1}^{s} C_i)^2} \tag{8}$$

In the above expressions, w_i is the weight of criteria *i* assigned by FCNP-VWA, C_i is the forwarding cost of the *i*th hop. FC_{route}^k and V_{route}^k are the forwarding cost and variance for the route of ant *k*, respectively. κ and δ are constant coefficients between 0 and 1 and $\kappa + \delta = 1$. As a result, the route with a lower forwarding cost and a lower variance has a larger evaluation function value.

The BS broadcasts Pheromone_Update_Msg( ) to the entire network so that the ants from each CH node update the pheromone of the edges of the CH nodes in m routes with the largest value of the evaluation function among the their routes. The CH nodes that received this message change the pheromone trail value in $[\tau_{min}, \tau_{max}]$ to improve the convergence rate. At this time, we use the adaptive change rule of evaporation coefficient and the reward and punishment mechanism for enhancing the convergence as in [6]. This procedure is repeated for given several iterations to find the best next relay CH which every CH adopts to relay data to BS. In this way, all the CH nodes determine the next hop CH node, and finally a routing tree from any CH node to the root node BS is constructed.

4.2. Data gathering phase

In the intra-cluster communication, for avoiding the collision generation if several CMs in a cluster transmit the sensed data to a CH simultaneously, the CH broadcasts schedule_Msg(·) message to its CMs at the start of the data gathering stage and allocates time slots for transmission. The CMs which obtain schedule-Msg(·) send the data to their CH nodes only during the time slot allocated to them and then get into the sleep mode to save energy. After the intra-cluster communication, the inter-cluster communication between CH nodes is performed through the constructed routing tree.

The complexity of the proposed scheme is the combination of that of FVT and improved max-min ACO i.e., FCNP-VWA-max-min ACO. Since the BS or SNs know the multi-criteria' weights determined by an advance estimate, the complexity of FCNP-VWA is not included within the total computational overhead. Thus, the combination of TOPSIS and max-min ACO determines the total time complexity of the proposed scheme. The pseudo code of an uneven clustering routing protocol using a hybrid FVT and improved max-min ACO is shown in Algorithm 1.

Algorithm 1. A decentralized uneven cluster-based routing protocol using a hybrid FVT and improved max-min ACO
Input: Set of alive SNs, weights of six criteria determined with FCNP-VWA, initialization parameters for max-min ACO
Output: An optimal routing tree
1: procedure FVE-ACO-UCR
2: BS broadcasts BS_start_Msg(·) and informs 6 criteria' weights allocated with FCNP-VWA to all SNs in the network;
3: Give and take Hello_Msg(·) between SNs and achieve criteria values of neighboring nodes;
4: Select CH nodes by FVT and broadcast CH_Msg(·) wthin contest radius;
5: Join suitable CH node by FVT and reply to Join_Msg(·);
6: CH nodes broadcast Next_Hop_CH_Msg (·) within $r\, R_i^{compe}$ to know ants location corresponding to the forward neighboring CH nodes;
7: while $t \leq Max\_Iter$ Do;
8: Calculate visibility value using (5) with the criteria' weights assigned by FCNP-VWA;
9: Calculate evaluation function values using (6)-(8) for *m* routes that each ant arrives to BS;
10: Select the route with the largest evaluation function value;
11: BS broadcasts Pheromone_Update_Msg( ) to update pheromone of edges of CH nodes in *m* routes;
12: end while
13: Form the routing tree from each CH node to BS;
14: end procedure

5. PERFORMANCE EVALUATION
5.1. Simulation setup

We perform extensive simulations on Matlab tool to assess the performance of the suggested scheme. In the extensive simulation, the performance of the suggested scheme named FVT-ACO-UCR is compared to UCR [1]. FVE-UCR [7] and UCFIA [6]. The simulation parameters are set as in Table 5. The parameters related to the improved max-min ACO are the same as those in [6]. Figure 1 shows the experimental network area with red points representing high importance locations like ways and battle places. In this figure, the appearing frequency of the targets within the red area is 2 times higher than that in the other positions.

Table 5. Simulation parameters

Parameter	Value
Network size	200×200m^2
Num of SNs	400
Position of BS	(250m.100m)
Incipient energy	0.5J
Data packet length	4000bit
Control packet length	200bit
E_{elec}	50nJ/bit
ε_{fs}	10pJ/bit/m^2
ε_{mpf}	0.0013pJ/bit/m^4
E_{DA}	5nJ/bit/Signal

5.2. Simulation results and analysis

Frist, the simulation in terms of RE variance (REV) metric is conducted. The REV is used for evaluating the variance of the remaining energy of all SNs in the network. At this time, the dead SNs are eliminated from the REV computation. Simulation results of REV according to the maximum competition radius (R_{max}) in Figure 2 show that FVT-ACO-UCR protocol has the smallest REV compared to the other protocols. The suggested protocol first determines multi-criteria' weights with FCNP-VWA, and then based on these assigned weights, completes the clustering step with TOPSIS, thus not magnifying the perception of the pairwise difference, also selecting CH more suitably than FVE-UCR and UCFIA. In addition, In FVT-ACO-UCR, the routing tree from CHs to base station is formed based on the improved max-min ACO.

Ordering the compared four protocols in terms of the REV, FVE-UCR follows the proposed protocol, UCFIA the third, and UCR the last. Although UCFIA uses the max-min ACO for the routing tree construction, it conducts the clustering by FL adopting only 3 criteria like RE, Dis and neighbor degree, so not choosing the CH more reasonably than FVT-ACO-UCR and not balancing the energy expenditure as much as FVT-ACO-UCR can achieve. Next, the simulation in terms of network lifetime (NL) metric which is denoted as the time till the first SN dies according to varying R_{max} is performed. Figure 3 shows the simulation results of NL.

From these results, we can see that network lifespan of FVT-ACO-UCR is the longest for all R_{max}. If R_{max} is 60, NL of FVT-ACO-UCR is 213.44%, 145.74% and 105.44% longer compared to UCR, UCFIA and FVE-UCR, respectively. FVE-UCR is next order and is superior over the compared protocols under all Rmax. This indubitably indicates that when the hybrid MCDM is used for the cluster-route fixation stage of the clustering routing protocol, it is far superior to the other protocols. The following protocol is UCFIA. UCR has the lowest NL because this protocol uses the RE for the CH selection, and also uses 2 criteria of RE and Dis for the construction of the routing tree.

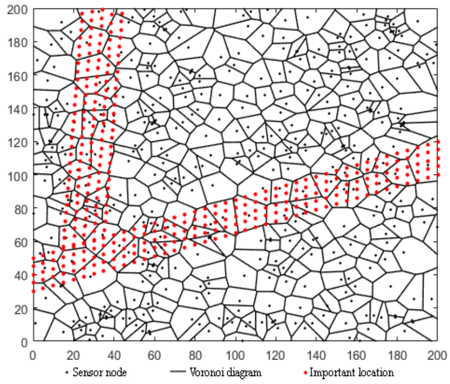

Figure 1. Experimental environment for simulation

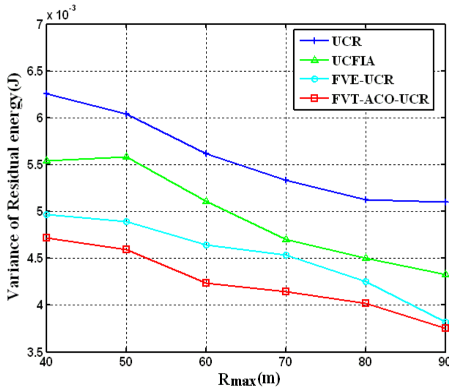

Figure 2. Comparison of residual energy variance by varying the maximum competition radius Rmax

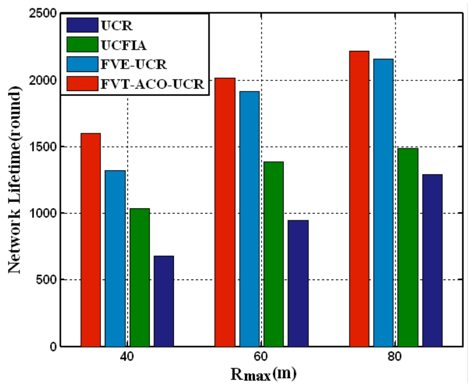

Figure 3. Comparison of network lifetime by varying R_{max}

6. CONCLUSION

The intention of optimum design combining the hybrid MCDM with meta-heuristic algorithms can be effectually adopted even when freely choosing other multi-criteria. In this paper, an energy-efficient clustering routing protocol is suggested, in which it employs a hybrid FVT to choose the CH nodes and forms the routes to BS by applying the improved max-min ACO. The proposed protocol prolongs the NL up to 213.44%, 145.74% and 105.44% in comparison with UCR, UCFIA and FVE-UCR protocols, respectively. However, the max-min ACO used in this paper is not the best meta-heuristic algorithm. We will try to combine a hybrid MCDM method with the other meta-heuristic algorithms such as EPO, artificial hummingbird algorithm (AHA) and capuchin search algorithm (CSA) to design the cluster-based routing protocol in our future work.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Man Gun Ri	✓	✓		✓	✓	✓		✓	✓	✓			✓	
Pyong Gwang Kim			✓		✓	✓		✓	✓	✓		✓		
Jin Sim Kim			✓	✓			✓			✓	✓		✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the article.

REFERENCES

[1] G. Chen, C. Li, M. Ye, and J. Wu, “An unequal cluster-based routing protocol in wireless sensor networks,” *Wireless Networks*, vol. 15, no. 2, pp. 193–207, 2009, doi: 10.1007/s11276-007-0035-8.

[2] A. A. Baradaran and K. Navi, “HQCA-WSN: high-quality clustering algorithm and optimal cluster head selection using fuzzy logic in wireless sensor networks,” *Fuzzy Sets and Systems*, vol. 389, no. 15, pp. 114–144, Jun. 2020, doi: 10.1016/j.fss.2019.11.015.

[3] Y. Chang, H. Tang, B. Li, and X. Yuan, “Distributed joint optimization routing algorithm based on the analytic hierarchy process for wireless sensor networks,” *IEEE Communications Letters*, vol. 21, no. 12, pp. 2718–2721, Dec. 2017, doi: 10.1109/LCOMM.2017.2756035.

[4] S. Sen, L. Sahoo, K. Tiwary, and T. Senapati, “Entropy weighted TOPSIS based cluster head selection in wireless sensor networks under uncertainty,” *Telecom*, vol. 4, no. 4, pp. 678–692, Oct. 2023, doi: 10.3390/telecom4040030.

[5] P. Rajpoot and P. Dwivedi, “Optimized and load balanced clustering for wireless sensor networks to increase the lifetime of WSN using MADM approaches,” *Wireless Networks*, vol. 26, no. 1, pp. 215–251, Jan. 2020, doi: 10.1007/s11276-018-1812-2.

[6] S. Mao and C. Zhao, “Unequal clustering algorithm for WSN based on fuzzy logic and improved ACO,” *The Journal of China Universities of Posts and Telecommunications*, vol. 18, no. 6, pp. 89–97, Dec. 2011, doi: 10.1016/S1005-8885(10)60126-4.

[7] M. G. Ri and C. H. Kim, “An uneven cluster-based routing protocol for WSNs using an integrated FCNP-VWA-ELECTRE,” in *2024 9th International Conference on Computer and Communication Systems (ICCCS)*, Apr. 2024, pp. 678–683, doi: 10.1109/ICCCS61882.2024.10603039.

[8] S. Janakiraman, M. D. Priya, A. C. J. Malar, and S. S. Jacob, “ELECTRE I-based zone head selection in WSN-enabled internet of things,” in *Proceedings of 3rd International Conference on Machine Learning, IoT and Big Data (ICMIB 2023)*, 2024, pp. 581–594, doi: 10.1007/978-981-99-3932-9_50.

[9] D. Mehta and S. Saxena, “Hierarchical WSN protocol with fuzzy multi-criteria clustering and bio-inspired energy-efficient routing (FMCB-ER),” *Multimedia Tools and Applications*, vol. 81, no. 24, pp. 35083–35116, 2022, doi: 10.1007/s11042-020-09633-8.

[10] P. S. Sreedharan and D. J. Pete, “A fuzzy multicriteria decision-making-based CH selection and hybrid routing protocol for WSN,” *International Journal of Communication Systems*, vol. 33, no. 15, Oct. 2020, doi: 10.1002/dac.4536.

[11] M. Gamal, N. E. Mekky, H. H. Soliman, and N. A. Hikal, “Enhancing the lifetime of wireless sensor networks using fuzzy logic LEACH technique-based particle swarm optimization,” *IEEE Access*, vol. 10, pp. 36935–36948, 2022, doi: 10.1109/ACCESS.2022.3163254.

[12] B. Priyalakshmi and S. Murugaveni, “Emperor penguin optimized Q learning method for energy efficient opportunistic routing in under WSN,” *Wireless Personal Communications*, vol. 128, no. 3, pp. 2039–2072, Feb. 2023, doi: 10.1007/s11277-022-10031-6.

[13] S. Pattnaik and P. K. Sahu, “Emperor penguin optimized clustering for improved multilevel hierarchical routing in wireless sensor networks,” in *Soft Computing: Theories and Applications*, 2021, pp. 13–25, doi: 10.1007/978-981-16-1696-9_2.

[14] M. A. Angel and T. Jaya, “An enhanced emperor penguin optimization algorithm for secure energy efficient load balancing in wireless sensor networks,” *Wireless Personal Communications*, vol. 125, no. 3, pp. 2101–2127, Aug. 2022, doi: 10.1007/s11277-022-09647-5.

[15] S. Singh, D. Garg, Manju, and A. Malik, “A novel cluster head selection algorithm based IoT enabled heterogeneous WSNs distributed architecture for smart city,” *Microprocessors and Microsystems*, vol. 101, Sep. 2023, doi: 10.1016/j.micpro.2023.104892.

[16] S. Chaurasia and K. Kumar, “ACRA: adaptive meta-heuristic based clustering and routing algorithm for IoT-assisted wireless sensor network,” *Peer-to-Peer Networking and Applications*, vol. 16, no. 5, pp. 2186–2201, 2023, doi: 10.1007/s12083-023-01505-w.

[17] R. Abraham and M. Vadivel, "An energy efficient wireless sensor network with flamingo search algorithm based cluster head selection," *Wireless Personal Communications*, vol. 130, no. 3, pp. 1503–1525, Jun. 2023, doi: 10.1007/s11277-023-10342-2.

[18] E. H. Houssein, M. R. Saad, E. Çelik, G. Hu, A. A. Ali, and H. Shaban, "An enhanced sea-horse optimizer for solving global problems and cluster head selection in wireless sensor networks," *Cluster Computing*, vol. 27, no. 6, pp. 7775–7802, Sep. 2024, doi: 10.1007/s10586-024-04368-9.

[19] Q. Tang and F. Nie, "Clustering routing algorithm of wireless sensor network based on swarm intelligence," *Wireless Networks*, vol. 30, no. 9, pp. 7227–7238, Dec. 2024, doi: 10.1007/s11276-023-03584-2.

[20] S. Chaurasia, K. Kumar, and N. Kumar, "EEM-CRP: energy-efficient meta-heuristic cluster-based routing protocol for WSNs," *IEEE Sensors Journal*, vol. 23, no. 23, pp. 29679–29693, Dec. 2023, doi: 10.1109/JSEN.2023.3322631.

[21] T. A. Alghamdi, "Energy efficient protocol in wireless sensor network: optimized cluster head selection model," *Telecommunication Systems*, vol. 74, no. 3, pp. 331–345, Jul. 2020, doi: 10.1007/s11235-020-00659-9.

[22] Z. Wang, J. Duan, H. Xu, X. Song, and Y. Yang, "Enhanced pelican optimization algorithm for cluster head selection in heterogeneous wireless sensor networks," *Sensors*, vol. 23, no. 18, Sep. 2023, doi: 10.3390/s23187711.

[23] I. B. Prasad, S. Gangwar, Yogita, S. S. Yadav, and V. Pal, "HCM: a hierarchical clustering framework with MOORA based cluster head selection approach for energy efficient wireless sensor networks," *Microsystem Technologies*, vol. 30, no. 4, pp. 393–409, Apr. 2024, doi: 10.1007/s00542-023-05508-8.

[24] S. K. Barnwal, A. Prakash, and D. K. Yadav, "Improved African bufalo optimization based energy efcient clustering wireless sensor networks using metaheuristic routing technique," *Wireless Personal Communications*, vol. 130, no. 3, pp. 1575–1596, Jun. 2023, doi: 10.1007/s11277-023-10345-z.

[25] M. G. Ri, I. G. Kim, S. H. Pak, N. J. Jong, and S. J. Kim, "An integrated MCDM-based charging scheduling in a WRSN with multiple MCs," *Peer-to-Peer Networking and Applications*, vol. 17, no. 5, pp. 3286–3303, 2024, doi: 10.1007/s12083-024-01705-y.

[26] J. S. Rim, M. G. Ri, S. H. Pak, and U. S. Kim, "FCVM(i): integrated FCNP-VWA-MCDM(i) methods for on-demand charging scheduling in WRSNs," *Journal of Data Science and Intelligent Systems*, vol. 3, no. 4, pp. 335–348, Sep. 2024, doi: 10.47852/bonviewJDSIS42023250.

BIOGRAPHIES OF AUTHORS

Man Gun Ri received the Ph.D. degree from DPR Korea, in 2006. He is currently a professor and the director of a research institute in the Faculty of Communications, Kim Chaek University of Technology, Pyongyang, Democratic People's Republic of Korea. His main research interests include computational intelligence, mobile computing and wireless sensor networks, routing protocols and optical networks. He can be contacted at email: rmg66412@star-co.net.kp.

Pyong Gwang Kim received the B.S. degree from DPR Korea, in 2019. He is currently pursuing the M.S. degree with the Faculty of Artificial Intelligence, Pyongyang University of Computer Technology, Pyongyang, Democratic People's Republic of Korea. His main research interests include wireless sensor networks. He can be contacted at email: kpg0313@star-co.net.kp.

Jin Sim Kim received the M. S. degree from DPR Korea, in 2014. She is currently a researcher in the International Technology Corporation Center, Kim Chaek University of Technology, Pyongyang, Democratic People's Republic of Korea. Her main research interests focus on artificial intelligence, metaheuristic modeling and optimization. She can be contacted at email: kjs8921@star-co.net.kp.