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An energy efficient cluster-based routing protocol using an integrated MCDM and EPO in WSNs

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ABSTRACT

Wireless sensor networks (WSNs) are widely applied in monitoring and communication but remain constrained by limited energy resources. Efficient routing protocols are critical to prolong network lifetime and ensure balanced energy consumption among sensor nodes. Traditional cluster-based routing often fails to achieve optimal energy balance, leading to premature node failures and degraded performance. Intelligent optimization algorithms, including meta heuristics such as particle swarm optimization (PSO) and emperor penguin optimization (EPO), have been applied to improve routing efficiency. These methods enhance convergence and adaptability but typically operate as standalone approaches. Limited attention has been given to integrating multi criteria decision making (MCDM) methods with meta heuristics. Without this integration, assigning precise weights to multiple criteria and balancing energy consumption across nodes remains difficult. This paper proposes a novel uneven cluster-based routing protocol that integrates fuzzy constrained nonlinear programming-variable weight analysis-technique for order preference by similarity to ideal solution (FCNP-VWA-TOPSIS) with an improved EPO. The protocol first assigns accurate weights to seven multi criteria using FCNP VWA and selects cluster heads (CHs) with TOPSIS. It then constructs the routing tree using improved EPO guided by the weighted fitness function. Extensive simulations show that the proposed protocol achieves superior energy balance, extending network lifetime by 158.0%, 119.3%, and 113.7% compared to uneven clustering routing (UCR), unequal clustering fuzzy logic intelligent algorithm (UCFIA), and fuzzy multi-criteria clustering and bio-inspired energy-efficient routing (FMCB ER), respectively. By combining MCDM and meta heuristic optimization, the protocol advances cluster-based routing in WSNs, significantly enhancing energy efficiency and reliability for real world applications.

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ABBREVIATIONS

ACO	Ant colony optimization
ASO	Atomic search optimization
AHP	Analytic hierarchy process
BS	Base station

CH	Cluster head
CM	Cluster member
ELECTRE	ELimination et choice translating reality
EPO	Emperor penguin optimization
FAHP	Fuzzy analytic hierarchy process
FMCB-ER	Fuzzy multi-criteria clustering and bio-inspired energy-efficient routing
FNCP	Fuzzy cognitive network processing
FVT-EPO-UCR	FCNP-VWA-TOPSIS-EPO-based uneven clustering routing
GA	Genetic algirithm
IoT	Internet of things
MCDM	Multi-criteria decision making
NEC	Network energy consumption
PROMETHEE	Preference ranking organization method for enrichment evaluation
PSO	Particle swarm optimization
QoS	Quality of service
REV	Residual energy variation
SDPR	Successfully delivered packet rate
SN	Sensor node
SSO	Shark smell optimization
TOPSIS	Technique for order preference by similarity to ideal solution
UCFIA	Unequal clustering fuzzy logic intelligent algorithm
UCR	Unequal clustering-based routing
UWSN	Underwater wireless sensor networks
VIKOR	VIsekriterijumska optimizacija i kompromisno resenje
VWA	Variable weight analysis
WSN	Wireless sensor network
WRSN	Wireless rechargeable sensor network

1. INTRODUCTION

A number of routing protocols have been developed and used for different applications so far. Now, among various routing protocols, a cluster-based routing protocol is the most attractive for energy-efficient utilization [1]–[7]. The energy-constrained wireless sensor networks (WSNs) are composed of a number of sensor nodes discriminated by mutually contradictory multi-criteria. Considering these characteristics of WSNs, there has been a growing interest in recent research on the application of intelligent optimization methods such as fuzzy logic or multi-criteria decision making (MCDM) and meta-heuristic algorithm to cluster-based routing [4]. There are several such protocols, including fuzzy logic-based [8], individual MCDM-based such as analytic hierarchy process (AHP) [9], visekriterijumska optimizacija i kompromisno resenje (VIKOR) [10], elimination et choice translating reality (ELECTRE) [11], technique for order preference by similarity to ideal solution (TOPSIS) [12], preference ranking organization method for enrichment evaluation (PROMETHEE) [13], the combination of intelligent optimization algorithms such as fuzzy logic, and ant colony optimization (ACO) [14]. Meanwhile, recently, the research results of improving further the charging performance by introducing an integrated MCDM methods such as (AHP-TOPSIS) [15], fuzzy analytic hierarchy process-variable weight analysis (FAHP-VWA-TOPSIS) [16], FAHP-VWA-Q-Learning [17], fuzzy constrained nonlinear programming (FCNP-TOPSIS) [18], and FCNP-Q-learning [19] to charging scheduling of WRSNs have been reported.

Clustering routing is usually performed by two phases, i.e., the cluster-route establishment phase and the data gathering phase. In the cluster-route establishment phase, the cluster head (CH) node is selected and the cluster member (CM) nodes are enlisted to the selected CH nodes to form clusters, and next hop CH nodes for relay data transmission between CH nodes are also selected to construct the routing tree. In the data gathering phase, the sensed data is transmitted through the constructed tree to base station (BS). The optimization goal of cluster-based routing is to maximize network lifetime by balancing the energy consumption between sensor nodes as much as possible while maintaining network stability, reliability and connectivity. Existing cluster-based routing protocols have mainly focused on using individual MCDM methods in the CH node selection of clustering phase.

What kind of intelligent optimization method is used to blend multi-criteria and what intelligent optimization methods are integrated are challenges to be addressed. However, so far, the researchers have not worked on combining MCDM methods with meta-heuristic algorithms so that energy consumption balance can maximally be provided in the cluster-route establishment phase. Research by Mao and Zhao [14], a protocol was proposed, which performs an uneven clustering with fuzzy logic and constructs a routing tree to

BS using max-min ACO. This protocol has the disadvantage of using only 3 criteria such as residual energy (RE), distance to BS and node neighboring degree (NND) as multi-criteria in fuzzy logic-based clustering. In addition, max-min ACO is not superior to other meta-heuristic algorithm such as emperor penguin optimization (EPO). Mehta and Saxena [20], a grid-based clustering scheme was proposed, which assigns the weights to multi-criteria by FAHP, selects CH nodes within the grid by TOPSIS, and uses the EPO to construct the routing tree from CH nodes to BS. However, this scheme can overestimate the actual pairwise difference between criteria in weight assignment due to the use of FAHP of the pairwise ratio scale. Furthermore, it doesn’t take into account the weight compensation to avoid the loss of resolution in weight evaluation when the weights of criteria have approximate values.

Fuzzy cognitive network processing (FNCP) is a MCDM method that uses fuzzy pairwise interval scale to solve the problem of uncertain importance evaluation arising from FAHP using fuzzy pairwise ratio scale [21]. FCNP, an ideal alternative to FAHP, can provide very reliable decision support compared to FAHP [22]. On the other hand, VWA is a method to adapt previously assigned weights based on state variable weight vectors [23], [24]. TOPSIS is a MCDM for selecting the alternatives and most commonly used in combination with other MCDM for weight allocation. We complete clustering in such a way that uses an integrated FCNP-VWA-TOPSIS. Here; i) FCNP first assigns to multi-criteria, ii) VWA compensates the weights of multi-criteria assigned by FCNP, and iii) TOPSIS selects the CH node and enlists CM nodes to the CH node with the compensated weights, thus the better energy consumption balance can be obtained in clustering.

On the other hand, the superiority of EPO over other meta-heuristic algorithms such as PSO and ACO has been demonstrated in several applied studies [20], [25]. A systematic review of the EPO, a recently developed meta-heuristic algorithm to solve a general optimization problem, was carried out in [26]. The main feature of EPO is that this method is based on a simple imitation of the huddling behavior of natural emperor penguins and provides a simple, straightforward implementation. In EPO, the emperor penguins represent candidate solutions, the clusters represent search spaces that constitute a two-dimensional L-shaped polygon plane, and the positions of emperor penguins represent feasible solutions. The focus of all the emperor penguins is to place an efficient mover representing the global optimal solution. Recently, EPO has been actively applied to address the optimization problem arising in many application fields.

The main objective of this work is to develop an uneven cluster-based routing protocol which can maximize the network lifetime. This goal is achieved by combining an integrated FCNP-VWA-TOPSIS and EPO to maximally provide the balanced and efficient utilization of the limited energy of all sensor nodes in the cluster-route establishment phase for WSNs. Here, uneven clustering refers to having CH nodes near BS with smaller clusters to alleviate the hot spot problem, which is caused because the closer to BS nodes are, the more relay burden of sensed data they receive [27]. The main contributions of this study are as follows:

- To our knowledge, this work is the first to exploit two integrated methods, FCNP-VWA-TOPSIS and FCNP-VWA-EPO, in the cluster-route establishment phase of uneven cluster-based routing protocol for WSNs.
- We propose an integrated FCNP-VWA-TOPSIS-based clustering method that achieves the optimum energy consumption balance, where TOPSIS selects the best optimal CH node and enlists CM nodes to the most appropriate CH node based on the correct weights allocated to the multi-criteria by FCNP-VWA.
- A routing tree construction method that optimally balances the energy consumption in the data gathering phase is proposed, which selects the next hop CH node most suitable for relay data transmission by the improved EPO using the weights of multi-criteria assigned by FCNP-VWA.
- Extensive experiment results have shown that the proposed protocol has much better performance than other existing protocols.

The rest of this paper is organized as follows. In section 2, the related works are discussed, and the network model and the energy consumption model is described in section 3. In section 4, the proposed protocol is described. The results of the extensive simulations and the analysis of them are presented in section 5 and this paper is concluded in section 6.

2. RELATED WORKS

In this section, we briefly review previous works on routing protocols using intelligent optimization algorithms among a number of cluster-based routing protocols. Baradaran and Navi [8], proposed the clustering method by selecting the optimal CH node in fuzzy logic using multi-criteria such as RE, minimum and maximum distance between nodes in each cluster, and minimum and maximum distances between nodes in each cluster and BS. A fuzzy logic-based two-level clustering and contents-based routing scheme was proposed in [28]. This scheme divides the whole network area into two levels to perform clustering and performs two routing processes according to the amount of data.

Lekhraj *et al*. [10] selected the CH node by VIKOR to perform clustering using seven multi-criteria such as CH node coverage, power, connectivity between BS and CH node, distance between BS and CH node, distances between CH node and sensor nodes, RE of node and node power. Janakiraman *et al*. [11] proposed a scheme to select a CH node with ELECTR-I using multi-criteria such as the number of times a node is selected as a CH node, the distance between node and CH node, the distances between neighboring nodes, and the energy level. A scheme to select CH node by TOPSIS using multi-criteria such as RE, number of neighbors, distance from BS, average distance (ADis) of CM nodes, distance ratio, and reliability is proposed by Sen *et al*. [12]. Rajpoot and Dwivedi [13], proposed the clustering scheme using individual MCDMs such as AHP, TOPSIS, and PROMETHEE with 16 mutually contradictory multi-criteria to provide the balance of load and energy consumption in clustering. In this scheme, 16 multi-criteria were chosen considering only the distance and energy factors by and large.

Hatamian *et al*. [29], proposed a centralized genetic-based clustering (CGC) scheme using onion method. This scheme uses genetic algirithm (GA) for choosing CH nodes and onion method for reducing the communication overhead between CH nodes in establishing the routes from CH nodes to BS. A scheme to construct a routing tree by performing an uneven clustering with fuzzy logic using three multi-criteria such as RE of nodes, distance to BS, and neighboring degree of nodes, and determining the appropriate next hop CH node using max-min ACO was proposed in [14]. Mehta and Saxena [20] proposed a grid-based clustering scheme to select a CH node with FAHP-TOPSIS by using multi-criteria of three broad parameters such as energy, QoS and distance, which have six sub-criteria, respectively. After completing clustering, the EPO was used to construct the route to BS in cluster-route establishment phase. Sreedharan and Pete [30], the authors proposed a scheme which selects the optimal CH node using the generalized intuitionistic fuzzy soft set (GIFSS) method and constructs the routing tree using the shark smell optimization (SSO) and genetic algorithm.

An enhanced flower pollination algorithm (FPA) based on the EPO was proposed to diagnose faults and extend network lifetime [31]. In this scheme, the optimal EPO (OEPO) algorithm was used to obtain automatic identification of the behavior of active sensor nodes, an alternative solution for repair of failed nodes and optimal routing. The enhanced FPA extends the stability period of the network by implementing load balancing and minimization of energy consumption of CH nodes in multi-hop communication between CH nodes and BS.

An opportunistic routing scheme using the EPO and Q-learning (EPO-Q) method was proposed for underwater wireless sensor networks (UWSNs) [32]. Void-hole generation and redundant packet transmission from sensor nodes to BS increase energy consumption and reduce the lifetime of UWSN. Therefore, this scheme avoids the void-hole problem and reduces energy dissipation by EPO-Q method. A hybrid EPO scheme was developed in [33] to solve three problems: load balancing, security enhancement, and energy consumption reduction. Combining the atomic search optimization (ASO) into hybrid EPO improves the updating function of EPO. Three main objective functions are considered to improve the performance of WSNs, such as load balancing, security enhancement, and energy consumption reduction. A bi-layered WSN architecture consisting of four steps: cluster formation, CH node selection, coverage hole detection and recovery, and routing was proposed in [34]. Using the K-means algorithm, it forms clusters and chooses a CH node by determined weight (DW). After clustering, it performs detection and recovery of coverage hole using fuzzy logic and uses multi-objective EPO (MO-EPO) algorithm for the best multi-hop route establishment. A maximum power point tracking (MPPT)-EPO based solar energy harvesting (EH) method was proposed for EH-WSN to maximize WSN network lifetime [35]. Using the energy efficient technique of the EPO algorithm, it optimizes the MPPT to track the optimal power from the solar panel. Thangaramya *et al.* [36] proposed a cluster formation and routing method based on neuro-fuzzy rule to improve the performance of WSN for IoT. For IoT using fog and cloud computing, an overlapping clustering scheme was proposed in [37]. This scheme chooses the best CH nodes to send the collected data to the closest fog nodes, which transmit the data to the cloud servers. It can be seen that the above considered routing protocols mainly use fuzzy logic or individual MCDM for clustering accompanied by CH node selection, and intelligent optimization methods such as ACO, EPO, and SSO for routing tree construction.

In making a summary on the issues of existing intelligent optimization-based routing protocols for WSNs, it is as follows. First, most of existing protocols using MCDM methods such as AHP or FAHP assigns the weights to multi-criteria using the pairwise ratio scale, thus magnifying the actual pairwise difference between multi-criteria. In addition, most of existing protocols using meta-heuristic algorithms such as GA, ACO, ASO, and EPO, assign equal weights to multi-criteria or cause uncertainty of subjective perception due to man-made unequal weighting in calculating fitness values. Finally, in constructing the routing tree, there has been no report on application of integrating MCDM methods with meta-heuristic algorithms. In this paper, we propose an uneven cluster-based routing protocol that uses an integrated FCNP-

VWA-TOPSIS to perform clustering, and EPO to construct a routing tree using the weights of multi-criteria assigned by FCNP-VWA.

3. SYSTEM MODEL
3.1. Network model
The assumptions for developing an uneven cluster-based routing protocol using the integrated MCDM and EPO are as follows:
- The network consists of N static sensor nodes randomly deployed in the square area of L×L, and an energy-constrained fixed BS located far away from the monitoring area.
- All sensor nodes have a limited capacity of unchangeable battery and unique ID, and they are heterogeneous and not aware of their location information.
- Sensor nodes can adjust their transmission power according to the distance between themselves and the receiver.

3.2. Energy expenditure model
We adopt the simple model proposed in [38] as an energy consumption model. The energy consumed to transmit the k bits data is calculated by (1).

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

where ε_{fs} and ε_{mpf} are the propagation loss coefficient, E_{elec} is the energy consumed for transmitting one bit data, and d is the transmission distance. In the equation, the power of d is determined by the transmission distance and the threshold distance $d_0=\sqrt{\varepsilon_{fs}S/\varepsilon_{mpf}}$=87.7 m.

The energy consumed for the reception of the k bits data is calculated using (2):

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

We assume that relay nodes do not aggregate incoming packets and only CH nodes collect data. Thus, when the energy consumed for the data aggregation is called E_{DA}, the total energy consumption of the CH node is expressed as (3):

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

4. PROPOSED PROTOCOL
The proposed protocol operates in two separate phases: cluster-route establishment phase and data gathering phase. The cluster-route establishment phase consists of clustering step in order to select the CH nodes and enlist CM nodes to the most appropriate CH nodes, and the routing tree construction step to establish the route to BS by selecting the next hop CH node for each single CH node. The clustering step uses an integrated FAHP-VWA-TOPSIS, while the routing tree construction step uses the improved EPO. In the data gathering phase, the data sensed in the whole network area are transmitted to BS through the routing tree. Figure 1 shows the systematic overview of the proposed protocol.

4.1. Cluster-route establishment
In this phase, BS first assigns the weights of multi-criteria characterizing the sensor nodes by FAHP-VWA and then notifies them the entire nodes in the network. The nodes within the network use these weights to form uneven and hierarchical clusters with TOPSIS in a distributed manner. As soon as clustering is completed, the CH nodes construct the routing tree by optimally determining the next hop CH node for relay data transmission using EPO.

4.1.1. Weighting of multi-criteria
In the weighting method by FCNP-VWA, node i is characterized using seven multi-criteria, such as RE, energy consumption rate (ECR), distance to BS (Dis), ADis to neighbors, NND, signal-to-noise ratio of link (SNR) and node location importance degree (NLID) [39]. The definitions of these criteria are as follows:

RE: this criterion is critical one in cluster-route establishment as it is one of the most important criteria characterizing the energy status of each sensor node. Once deployed within the network, sensor nodes get to know their RE by monitoring them.

ECR: this criterion, which represents the RE change over a certain time period, is also an important one that reflects the energy consumption status of each node. Due to the uneven traffic load on each node, the ECR varies with time, so it should be able to measure this criterion in a real-time way. In this paper, the ECR for each node is calculated according to [40].

$$\begin{cases} ECR_i(n) = \frac{ECR_i(n-1)\times TS(n-1)+ecr_i(n)t(n)}{TS(n-1)+t(n)} \\ ECR_i(1) = ecr_i(1) = \frac{E_i^{res}(0)-E_i^{res}(1)}{\Delta} \end{cases} \tag{4}$$

where, $ECR_i(n)$ is the ECR in the nth measurement interval of node i, Δ -the RE measurement interval, $TS(n-1)$ -the sum of the total time to the (n-1)th measurement interval, $ecr_i(n)$ -the real-time ECR in the nth measurement interval of node i, and $E_i^{res}(0)$ -the RE in the 0th measurement interval, i.e., the energy capacity of node i.

Distance to BS (Dis): it is calculated by the Euclidean distance between nodes $i(x_i, y_i)$ and BS(x_{BS}, y_{BS}) denoted as (5):

$$d_{i,BS} = \sqrt{(x_i - x_{BS})^2 + (y_i - y_{BS})^2} \tag{5}$$

ADis to neighbors: it means the average of the distance to all neighbors within the communication radius of node i. The smaller $D_{i,nei}^{aver}$ is, the larger power is consumed in communication between nodes.

$$D_{i,nei}^{aver} = \frac{\sum_{j=1}^{n_i} D_{i,j}}{n_i}, (i \neq j) \tag{6}$$

Here, n_i denotes the number of neighbors within the communication radius of node i, while $D_{i,j}$ denotes the distance between node i and its neighbor j.

NND: this criterion is used for identifying the number of neighbors within the communication radius of node i, which is expressed as (7):

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

Here, n_i denotes the number of neighbors within the communication radius of node i, while n_{max} denotes the maximum number of neighbors within the communication radius at the location of any nodes in the network.

The SNR of link: the signal-to-noise ratio of link of node i is calculated by (8) [41]:

$$SNR_i = 10\, log_{10}(\frac{P_i^{signal}}{P_i^{noise}}) \tag{8}$$

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

NLID: this criterion reflects the importance degree of each grid when the whole monitoring area of the network is divided into a number of discrete grids [39]. The importance of the grid is defined as advent frequency of the monitoring object occurring within the grid. In the network with n sensor nodes, the location importance degree of node i $NLID_i(t)$ is expressed as (9):

$$NLID_i(t) = min\{C \times w_i(t) \times N/\phi, 1\} \tag{9}$$

Here, w_i is the weight of Voronoi region of the grid g_{ij}, and ϕ is the total amount of maximum surveillance efficiency of each grid, respectively, expressed as (10) and (11):

$$w_i(t) = \sum_{g_{ij}\in \Xi_i} \phi_{ij}(t) \tag{10}$$

$$\phi = \sum_{g_{ij}\in D} max(\phi_{ij}(t)) \tag{11}$$

In the equations, $\phi_{ij}(t) = 1 - e^{-a_{ij}}[1 - \phi_{ij}(t-1)]$ (here, a_{ij} is the importance degree of the grid g_{ij}) is the surveillance efficiency of the grid g_{ij}. C is a perspective factor ($C \in [0,10]$) that takes into account the influence of environmental changes such as topology, node failure, and the wrong prior knowledge of each grid, and it is expressed as (12) using the frequency detected during the time period t.

$$C = 10 \times (\frac{h}{N})^4 \tag{12}$$

The location importance degree of each node is determined for each node in advance. Weighting to the above considered criteria is proceeded by FCNP-VWA.

FCNP is a method to assign weights to multi-criteria using fuzzy numbers such as triangular fuzzy numbers on fuzzy pairwise interval scales. A fuzzy pairwise interval scale-based fuzzy pairwise opposite matrix (FPOM) is constructed using triangular fuzzy numbers. The fuzzy accordance index ($\hat{AI}$) for FPOM is verified. From the consistency-verified FPOM, the vector of fuzzy individual utility is obtained from the fuzzy primitive least squares (FPLS) optimization model, and then normalized to obtain the fuzzy weight vector of the criteria. An overview of weighting multi-criteria by FCNP is in [17], [18].

VWA is a weight compensation method that automatically emphasizes or weakens the weights assigned by FCNP according to their importance degree using a state variable weight vector. In FCNP, unlike in FAHP, the exponent type state variable weight vector with penalty is used. In FAHP using the pairwise ratio scale, the exponent type state variable weight vector with incentive is used to increase the criterion's weight as the state value increases. However, the exponent type state variable weight vector with penalty increases the criterion's weight as the state value decreases. In other words, the criterion balancing requirement of decision making is realized by penalizing the low-level criteria. A review of VWA is described in [42], [43].

The fuzzy pairwise opposite matrix for determining the relative weights of the multi-criteria considered above is shown in Table 1. The accordance verification result for this fuzzy pairwise opposite matrix is $AI = 0.0893$. Since $0 < AI < 0.1$, so the consistency is satisfied. The normalized weights assigned to each criterion by FCNP and the compensated weights by VWA in case that the value of the state variable vector α was set to 0.75 are shown in Table 2.

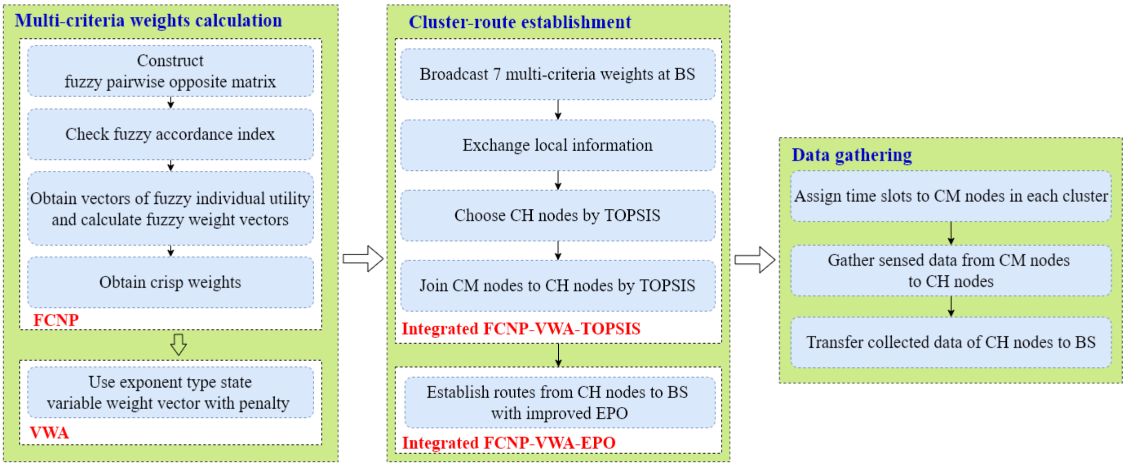

Figure 1. Overview of the proposed protocol

Table 1. The fuzzy pairwise opposite matrix between criteria

Evaluation criteria	RE	ECR	Dis	ADis	NND	SNR	LNID
RE	0	3^+	0	4^+	4^+	6^+	6^+
ECR	3^-	0	3^-	2^+	2^+	3^+	3^+
Dis	0	3^+	0	4^+	4^+	6^+	6^+
ADis	4^-	2^-	5^-	0	0	4^+	4^+
NND	4^-	2^-	5^-	0	0	4^+	4^+
SNR	6^-	3^-	6^-	4^-	4^-	0	2^+
LNID	6^-	3^-	6^-	4^-	4^-	2^-	0

Table 2. Compensated weight of evaluation criteria

Criteria	Weight (w_i)	Compensated weight (w_i)
RE	0.1845	0.1898
ECR	0.1480	0.1351
Dis	0.1845	0.1965
ADis	0.1390	0.1502
NND	0.1390	0.1105
SNR	0.1048	0.1089
LNID	0.1002	0.1090

4.1.2. Cluster formation

At the beginning of the protocol, BS begins clustering by broadcasting BS_start_Msg (w_1, …, w_7, $d_{i,j}^{max}$, $d_{i,j}^{min}$) in the whole network to notify all sensor nodes the weights of multi-criteria. All the nodes which have received this message get to know the distance to BS using the Received Signal Strength Intensity (RSSI).

At the beginning of each round of this protocol, all the nodes exchange their local information to select the CH node by broadcasting Hello_Msg (i, E_i^{res}, $d_{i,BS}$, ECR_i, $NLID_i$, R_i^{compe}).

In this message, *i* denotes the ID of node *i*, $d_{i,BS}$-the distance between node *i* and BS, E_i^{res}-the RE of node *i*, and $NLID_i$-the location importance degree of node *i*. R_i^{compe} denotes the competition radius of node *i* and is calculated using (13):

$$R_i^{compe} = (1 - \gamma \times \frac{d_{i,j}^{max} - d_{i,BS}}{d_{i,j}^{max} - d_{i,j}^{min}}) \times R_i^{max} \quad (13)$$

where γ takes the value of the interval [0,1] as a constant coefficient, and R_{max} is the predefined maximum competitive radius.

Through the exchange of Hello_Msg(·), the nodes get to know the neighboring degree NND_i of themselves and calculate the ADis to the neighbors $D_{i,nei}^{aver}$ and the signal to noise ratio SNR_i. As soon as the nodes gather local information, they proceed the data dimension normalization of their quantitative criteria' values in the same way as in [9].

When we call the set of nodes V, the normalization of the evaluation value ($\tilde{x}_{ij}$) of the criterion j of the node *i* is proceeded as (14):

$$x_{ij} = \frac{\tilde{x}_{ij} - \min_{k \in V}(\tilde{x}_{kj})}{[\frac{1}{N}\sum_{k \in V}(\tilde{x}_{kj} - \frac{1}{N}\sum_{l \in V}\tilde{x}_{lj})^2]^{1/2}}, i = \overline{1, N}; j = \overline{1, M} \quad (14)$$

When the exchange of nodes' local information is completed, each node initiates the CH competition. At this time, each node uses an integrated FCNP-VWA-TOPSIS to select the CH node and enlist CM nodes into the CH node. To do this, first, a decision matrix which will be used in TOPSIS is constructed.

When a sensor node receives Hello_Msg(·) messages from five neighboring nodes, an example of the normalized six criteria' values for a total of six sensor nodes including itself is shown in Table 3.

The decision matrix to be used in TOPSIS is shown in Table 4. The sensor nodes with high E_i^{res}, short $D_{i,BS}$, low ECR_i, high NND_i, short $D_{i,nei}^{aver}$, high SNR_i, and low $NLID_i$ are selected as a CH node with higher probability.

Then the upper bound (positive ideal solution) and the lower bound (negative ideal solution) of the solutions are calculated as in Table 5. The separations between the upper bound and the lower bound are calculated, and the relative closeness to the upper bound is calculated for each sensor node then based them, the priority is determined as shown in Table 6.

Table 3. Criteria values of sensor nodes

Evaluation criteria	RE	ECR	Dis	ADis	NND	SNR	LNID
SN1	1.6565	3.1854	0.8730	1.6036	5.4258	1.8688	1.7088
SN2	2.8169	4.6786	1.5703	2.4054	4.2531	1.0511	1.2565
SN3	1.5251	2.3891	3.7058	0.8018	5.1055	2.6279	3.9202
SN4	2.1015	3.0859	1.6620	1.6036	3.7074	2.2191	1.9601
SN5	3.3145	4.4795	3.2688	2.4054	6.4090	3.2119	0.9047
SN6	4.3761	5.1763	2.6327	4.0089	6.3639	4.2047	2.7140

Table 4. Reconstructed decision matrix

Evaluation criteria	RE	ECR	Dis	ADis	NND	SNR	LNID
SN1	0.3145	0.4303	0.1716	0.2408	0.5993	0.2035	0.1863
SN2	0.5347	0.6321	0.3086	0.3613	0.4698	0.1145	0.1370
SN3	0.2895	0.3228	0.7283	0.1204	0.5640	0.2862	0.4273
SN4	0.3989	0.4169	0.3266	0.2408	0.4095	0.2417	0.2136
SN5	0.6292	0.6052	0.6424	0.3613	0.7079	0.3498	0.0986
SN6	0.8307	0.6993	0.5174	0.6021	0.7030	0.4579	0.2958

Table 5. Positive and negative ideal solutions

Ideal solution	RE	ECR	Dis	ADis	NND	SNR	LNID
Upper bound	0.3145	0.4303	0.1716	0.2408	0.5993	0.2035	0.1863
Lower bound	0.5347	0.6321	0.3086	0.3613	0.4698	0.1145	0.1370

Table 6. Priorities of SNs

Sensor node	d_i^*	d_i^0	C_i^*	Priority
SN1	0.7191	0.6893	0.4895	4
SN2	0.6189	0.6632	0.5172	2
SN3	0.9981	0.4382	0.3051	6
SN4	0.6402	0.6469	0.5026	3
SN5	0.7077	0.5942	0.4564	5
SN6	0.6216	0.8394	0.5745	1

In this way, all the nodes calculate C_i^* representing the priority for neighboring nodes and themselves. If a certain node has neighboring node(s) with larger C_i^* than its, it discards CH competition and becomes CM node. If its C_i^* is the largest, it broadcasts CH_Msg(·) within the competitive radius R_i^{compe} to declare that it has become the CH node. The nodes which received CH_Msg(·) response to it with Join_Msg(·) in order to inform that they have become the CM nodes of the CH node.

When nodes receive more than two CH_Msg(·) messages, they enlist in the most suitable CH node using FCNP-VWA-TOPSIS as in CH node selection. In other words, the CH node with values of larger E_i^{res}, shorter $D_{i,BS}$, lower ECR_i, higher NND_i, shorter $D_{i,nei}^{aver}$, higher SNR_i, and lower $NLID_i$ is the most suitable CH node and enlist the CH node. Such a CH node has value of the largest relative closeness to the positive ideal solution C_i^*. The node which receives no CH_Msg(·) for a certain time declares itself as a CH node.

4.1.3. Routing tree construction

The proposed protocol constructs the routing tree that is the route for transmitting the sensed data to BS via relays between CH nodes. As soon as the clusters are formed, CH nodes broadcast NextHop_CH_Msg (i,E_i^{res},ECR_i,$D_{i,BS}$,NND_i,$D_{i,nei}^{aver}$,SNR_i,$NLID_i$) within mR_i^{compe}, where m is the minimum integer that allows any CH node to contain at least one neighboring CH node according to [27]. Through the broadcast of NextHop_CH_Msg(·), all the CH nodes get to know the forward neighboring CH nodes whose distance to BS is shorter than that of itself.

First, the fitness values of each CH node to find the optimal route from the CH nodes to BS are calculated. The fitness function for this $FV(CH_i)$ is defined exploiting all 7 multi-criteria used in clustering, unlike previous studies where only RE and distance to BS were used as the main factors.

$$\mathrm{FV}(CH_i) = \sum_{j=1}^{7} w_j\, C_j = w_1 \frac{E_i^{cap} - E_i^{res}}{E_i^{cap}} + w_2 \frac{D_{i,BS}}{max\ D_{i,BS}} + w_3 \frac{ECR_i}{max\ ECR_i} + \\ + w_4 \frac{D_{i,nei}^{aver}}{max\ D_{i,nei}^{aver}} + w_5 \frac{max\ NND_i - NND_i}{max\ NND_i} + w_6 \frac{max\ SNR_i - SNR_i}{max\ SNR_i} + w_7 \frac{NLID_i}{max\ NLID_i} \quad (15)$$

Here, w_j denotes the weight assigned by FCNP-VWA to 7 multi-criteria, $max\ x$ -the maximum value of the corresponding x criterion, and E_i^{cap}-the energy capacity of CH_i. From (15), it can be seen that CH nodes with high E_i^{res}, short $D_{i,BS}$, low ECR_i, small NND_i, short $D_{i,nei}^{aver}$, high SNR_i, and low $NLID_i$ can be the next hop CH node. In the previous works related to exploitation of EPO in routing of WSNs, only RE and distance to BS were used as the main factors. Unlike previous works, however, the values of 7 factors or criteria were taken into account in determining the next hop CH node. In addition, these criteria have accurate weights assigned by FCNP-VWA according to their importance degree, not fair weights. The improved EPO considers not only RE and distance ($D_{i,BS}$ and $D_{i,nei}^{aver}$), but also change of ECR, the number of neighboring nodes, link's quality and target advent frequency, therefore choosing the optimal next hop CH node.

Each CH node uses EPO to construct a routing tree to BS as follows. First, every single CH node randomly selects neighboring CH nodes within mR_i^{compe} of its forward neighboring CH nodes. This corresponds to the occurrence and determination of the emperor penguin huddle boundary in EPO. At this time, the gradient within the network area of neighboring CH nodes is used. In other words, these gradients (ψ) specify the forward neighboring CH nodes (ϕ).

$$\psi = \nabla\phi \tag{16}$$

When the analytic function for the sensor network area is called F, it is associated with a vector κ and is expressed as a complex potential:

$$F = \phi + i\kappa \tag{17}$$

where i is the imaginary constant. Finally, the forward neighboring CH nodes with high gradient within mR_i^{compe} are chosen, thus saving energy and improving network lifetime.

Next, the energy among the selected forward neighboring CH nodes is calculated. This corresponds to the calculation of temperature profile around the emperor penguin huddle in EPO. To this end, the exploitation and exploration process are performed for the selected forward neighboring CH nodes. Through the computation of this energy profile, the RE of the forward neighboring CH nodes is identified. The energy profile is calculated as (18) and (19):

$$RE' = (RE - \frac{Max_{iteration}}{x - Max_{iteration}}) \tag{18}$$

$$RE = \begin{cases} 1, for\ r > 1 \\ 0, for\ r < 1 \end{cases} \tag{19}$$

Here, x denotes the current iteration, and $Max_{iteration}$-the maximum number of iterations, and r -the iteration that must transmit the corresponding data packet, respectively. In (19), the energy value is calculated as 1 if the number of iterations that must send a data packet is greater than 1, and as 0 if the number of iterations is less than 1.

Consecutively, the proposed routing tree construction method determines the current best CH node by calculating the distance between the selected forward neighboring CH nodes.

$$\vec{D}_{CH} = Abs(SF(\vec{A}) \cdot \vec{L}(x) - \vec{B} \cdot \vec{L}_{CH}(x)) \tag{20}$$

Here, $\vec{D}_{CH}$ denotes the distance between the given CH node and the best CH node, i.e., its fitness value is the largest CH node, and x indicates the current iteration. $\vec{L}$ and $\vec{L}_{CH}$ denotes the position vectors of the best optimal solution and the CH node, respectively, and $SF()$ represents the social forces that change the position of themselves towards the best optimal solution. $\vec{A}$ and $\vec{B}$ are vectors used for collision avoidance, which are expressed as (21)-(23):

$$\vec{A} = MP \times (RE' + NET_{grid}(Accuracy)) \times Rnd()) - RE' \tag{21}$$

$$NET_{grid}(Accuracy) = Abs(\vec{L} - \vec{L}_{CH}) \tag{22}$$

$$\vec{B} = Rnd() \tag{23}$$

Here, MP is a parameter used to maintain the gap between exploration agents for collision avoidance, where is set to 2. The grid accuracy, $NET_{grid}(Accuracy)$ is used to compare the distance difference between CH nodes, and is a random number between 0 and 1. The best optimal CH node is selected through the exploitation and exploration process:

$$SF(\vec{A}) = (\sqrt{h \cdot e^{-x/m} - e^{-x}}) \tag{24}$$

Here, e is exponential function, h and m are the control parameters for better exploitation and exploration while their range of values lies between [2,3], [1,5,2], respectively. The exploration process indicates the optimal CH node initially obtained to transmit the data packet with all satisfied aspects, and the exploitation process means the best CH node obtained after the exploration process.

Finally, mover is reassigned. This corresponds to updating the position of the forward neighboring CH nodes with the CH node i.e., mover in EPO, at the best optimal position obtained.

$$\vec{L}_{CH}(x+1) = \vec{L}(x) - \vec{A} \cdot \vec{D}_{CH} \quad (25)$$

Here, $\vec{L}_{CH}(x+1)$ denotes the updated next position of the CH node. The next position of the CH node for data packet transmission is updated in this way, and such process is performed repeatedly until the route to BS is obtained.

4.2. Data gathering phase

First, the intra-cluster communication where all the CM nodes transmit sensed data to its CH node is performed. To avoid the collision when multiple CM nodes within a cluster transmit sensed data simultaneously to a CH node, the CH node sends Schedule_Msg(·) to its CM nodes at the beginning of data gathering phase and assigns transmission time slots. The CM nodes that receive Schedule_Msg(·) transmit sensed data to its CH node only during the time slot assigned to them and then switch to sleep mode for saving energy. If any CM node does not transmit the sensed data during the assigned time slot in the current round, its CH node decides the CM node does not have any data to be transmitted or the CM node already died. In this case, CH node does not assign time slot for the CM node in scheduling of the next round. After the intra-cluster communication, the CH nodes perform the infusion processing including data redundancy removal and data compression. After that, the inter-cluster communication between CH nodes is proceeded through the constructed routing tree and the sensed data is transmitted to BS. Algorithm 1 shows the pseudo code of an uneven cluster-based routing protocol using an integrated FCNP-VWA-TOPSIS and improved EPO.

Algorithm 1. A distributed uneven cluster-based routing protocol using an integrated FCNP-VWA-TOPSIS and improved EPO

Input: Set of alive sensor nodes, weights of 7 criteria determined by FCNP-VWA, Initialization parameters for EPO

Output: An optimally constructed routing tree

1: **procedure** FVE-EPO-UCR
2: BS broadcast BS_start_Msg(w_1,…,w_7,$d_{i,j}^{max}$, $d_{i,j}^{min}$) and inform 7 multi-criteria' weights assigned by FCNP-VWA to sensor nodes;
3: Exchange Hello_Msg(·) between sensor nodes and obtain 7 criteria values of neighbors;
4: Choose CH nodes with TOPSIS and broadcast CH_Msg(·) in competitive radius;
5: Enlist proper CH node with TOPSIS and response to Join_Msg(·);
6: Call EPO algorithm in [25] using fitness function of (15) to choose the next optimal CH node;
7: Construct the routing tree from each CH node to BS;
8: CH node send Schedule_Msg(·) to its CM nodes;
9: **end procedure**

5. PERFORMANCE EVALUATION

5.1. Simulation setup

We conduct extensive simulations on MATLAB 2020a to evaluate the performance of the proposed protocol named FVT-EPO-UCR. The performance of the proposed protocol called FVT-EPO-UCR is compared with UCR [27], UCFIA [14], and FMCB-ER [20]. In the simulation experiment, sensor nodes (SNs) from 100 to 300 are randomly placed in 200×200 m^2 area and BS is fixed at (250, 100). The size of the data packet and the control packet is 4000 bits and 200 bits, respectively. The grid, which is the effective monitoring area of each sensor node, is represented by a polygon defined by Voronoi diagram. The whole network area with red dots indicating locations of high importance such as roads and battle fields is shown in Figure 2. In the simulation, the frequency of targets appearing in the red regions is two times higher than in the other locations. For fair comparison, a gird-based clustering of FMCB-ER is converted to uneven clustering scheme of other three comparative protocols to confirm clustering scheme of all comparative protocols. A constant coefficient γ in (13) denoting the competition radius for uneven clustering is set to 0.3 [27]. The other parameters are set as in Table 7.

The following performance metrics are used to evaluate the performance of cluster-based routing protocols:

- Network energy consumption: this metric is defined as the amount of energy consumed by all sensor nodes in the network.
- Residual energy variation: it is a metric evaluating the RE variance of all nodes in the network. Then, the already dead nodes are excluded from this calculation.
- Successfully delivered packet rate: it denotes data packets successfully transported to BS over the total number of packets sent by CM nodes.
- Network lifetime: it is defined as the time till the first sensor node dies under the different number of SNs.

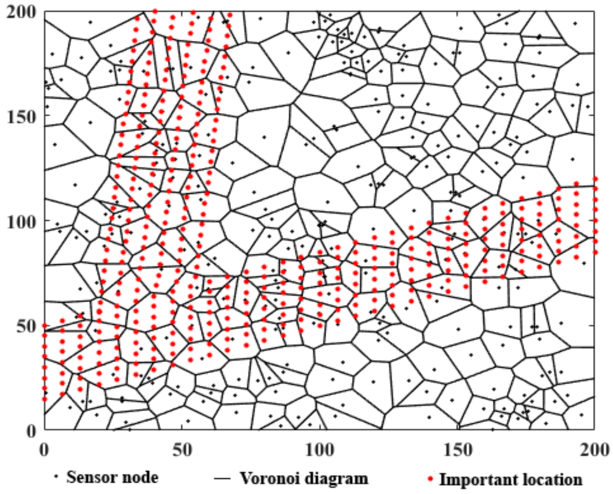

Figure 2. Sensor nodes and its Voronoi diagram and important locations with red points

Table 7. Simulation parameters

Parameter	Value
Network size	200×200 m^2
Number of nodes	100-300
Location of BS	(250 m, 100 m)
Initial energy	2 J
Length of data packet	4000 bits
Length of control packet	200 bits
Eelec	50 nJ/bit
ε_{fs}	10 pJ/bit/m^2
ε_{mpf}	0.0013 pJ/bit/m^4
EDA	5 nJ/bit/signal

5.2. Simulation results and analysis

The experimental results were obtained with 20 times of simulated averages without unbiased comparison.

5.2.1. Network energy consumption

This simulation was conducted under the equal condition in terms of all compared protocols. A smaller network energy consumption represents that the corresponding routing protocol utilizes the given energy more effectively. From simulation results shown in Figure 3 and Table 8, it can be seen that the proposed protocol consumes the smallest amount of energy by varying the number of sensor nodes (SNs) for performing the surveillance tasks. For 300 of the number of SNs, the proposed protocol consumes less amount of energy than 15 mJ, but UCR, UCFIA and FMCB-ER protocols consume more energy of 34 mJ, 23 mJ, and 17 mJ than the proposed, respectively. Less energy consumption in executing the proposed protocol implies that the sensor nodes operating according to this protocol can operate during longer rounds than when using other protocols of more energy consumption. This is because of exploiting an integrated

FCNP-VWA-TOPSIS and the improved EPO, and achieving the optimum energy consumption balance in the cluster-route establishment phase.

FMCB-ER protocol comes the next of the proposed. This result hints that FMCB-ER exploiting FAHP-TOPSIS and EPO consumes less energy than UCFIA using fuzzy logic and max-min ACO. From this result, we can see that from the viewpoint of energy consumption, an integrated FAHP-TOPSIS is superior to fuzzy logic and EPO is superior to max-min ACO when using an integrated FAHP-TOPSIS and fuzzy logic in selecting CH nodes, and EPO and max-min ACO in constructing the routing tree, respectively. UCR shows the biggest energy consumption. It is because this protocol uses not only the RE to select the CH node, but also two criteria of the RE and distance to BS to construct a routing tree without introducing any meta-heuristic, thus consuming more energy.

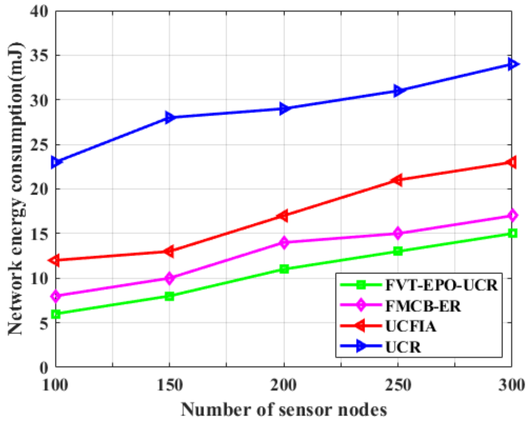

Figure 3. Comparison of network energy consumption with varying the number of SNs

Table 8. Network energy consumption (mJ)

Number of sensor nodes⇨Protocol⇩	100	150	200	250	300
FVT-EPO-UCR	6.0023	7.9822	11.0136	12.9924	15.0282
FMCB-ER	8.0105	10.1017	13.9198	15.0122	17.1712
UCFIA	11.9749	13.1042	17.0429	20.9920	23.1238
UCR	23.1062	27.9201	28.8921	31.0203	34.0671

5.2.2. Residual energy variation

This metric reveals balance and fairness of energy consumption of each sensor node. A smaller RE variation indicates better balance and fairness of energy consumption. Varying the number of SNs, simulation results of residual energy variance (REV) are shown in Figure 4 and Table 9. These results show that the REV of proposed protocol is the smallest compared to other protocols. In simulation results, when the number of SNs is 300, the proposed protocol shows the REV of 44.1%, 65.2%, and 88.2% compared to UCR, UCFIA, and FMCB-ER, respectively. The reasons are as follows: the proposed protocol primarily assigns weights to multi-criteria by FCNP-VWA, and then completes the clustering step with TOPSIS based on these weights. FCNP uses fuzzy pairwise interval or differential scale to address the issue magnifying the actual pairwise difference in FAHP. Moreover, in the proposed protocol, the assigned weights are compensated by VWA to avoid the resolution loss in weighting for criteria with similar evaluations. This results in more accurate criterion-by-criterion weights can be obtained. Thus, this protocol not only does not magnify the perception of the pairwise difference, but also selects more reasonable CH node than FMCB-ER and UCFIA protocols using FAHP and fuzzy logic, respectively. In addition, the proposed protocol constructs the routing tree from CH nodes to BS using the improved EPO. At this time, the fitness values of CH nodes are calculated to exploit 7 multi-criteria used in clustering unlike previous works where only RE and distance to BS are used as the main factors. Thus, it balances the energy consumption of each node by jointly considering multi-criteria in the whole process of clustering routing.

Ranking three previous protocols in terms of the REV by varying the number of SNs, FMCB-ER comes the next, UCFIA the third, and UCR the last. That is, FMCB-ER protocol follows the proposed protocol and indicates smaller REV than other two comparative protocols. This is because of using an integrated MCDM method, the FAHP-TOPSIS and constructing the routes from CH nodes to BS with EPO.

However, though UCFIA uses a meta-heuristic named the max-min ACO to construct a routing tree, it realizes the clustering with fuzzy logic using only three criteria such as RE, distance to BS and neighboring degree. Thus, it does not choose the CH node than FMCB-ER more reasonably and does not balance the energy consumption as much as FMCB-ER achieves.

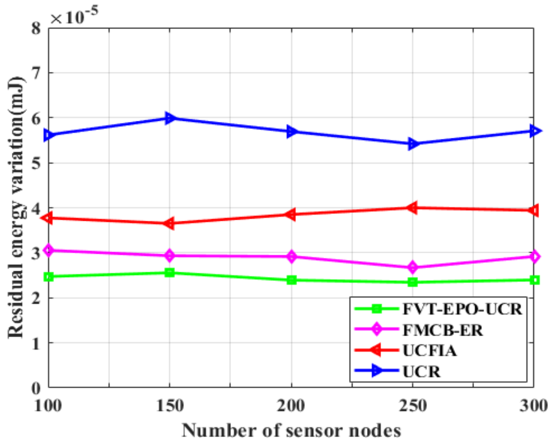

Figure 4. Comparison of RE variance with varying the number of SNs

Table 9. RE variation (mJ)

Number of sensor nodes⇨Protocol⇩	100	150	200	250	300
FVT-EPO-UCR	2.473e-5	2.393e-5	2.555e-5	2.344e-5	2.397e-5
FMCB-ER	3.055e-5	2.934e-5	2.917e-5	2.669e-5	2.918e-5
UCFIA	3.774e-5	3.651e-5	3.849e-5	4.000e-5	3.941e-5
UCR	5.615e-5	5.989e-5	5.693e-5	5.419e-5	5.707e-5

5.2.3. Successfully delivered packet rate

The simulation results of successfully delivered packet rate are shown in Figure 5 and Table 10. From these simulation results, it can be seen that SDPR of the proposed protocol is the highest. When the number of SNs is 200, the SDPR of the proposed protocol is 0.902. This is higher value of 123.3%, 111.8%, and 103.5% compared to the existing schemes, UCR, UCFIA, and FMCB-ER, respectively. It is due to using a SNR criterion in the proposed protocol. In other words, the sensor node with higher SNR has higher possibility which can be chosen to CH node and CH node with higher SNR is chosen to the next CH node with higher probability. Thus, this protocol increases the successfully delivered rate of the sensed data packet. FMCB-ER follows the proposed protocol because this protocol also uses three criteria or factors such as node energy, intra-cluster distance and restart number in evaluating the quality of service (QoS) of link between nodes.

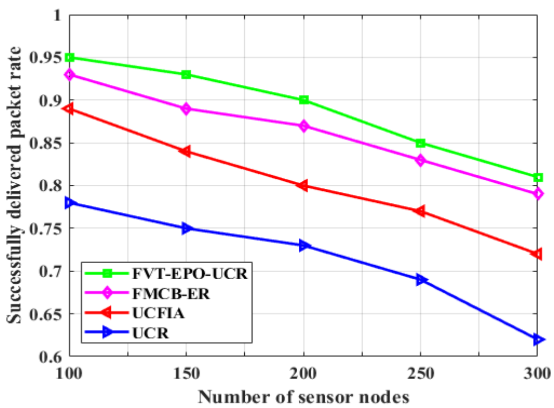

Figure 5. Comparison of successfully delivered packet rate with varying the number of SNs

Ranking the rest two compared protocols in terms of this metric, UCFIA comes the next of FMCB-ER and UCR is the last order. However, the difference of this criterion between two protocols is not so big. As considered in the related works, UCFIA uses three multi-criteria such as RE of nodes, distance to BS, and neighboring degree of nodes.

This protocol uses these criteria to choose CH nodes by fuzzy logic and constructs the routing tree by max-min ACO. Thus, it considers the link QoS's influence to a certain extent. However, UCR does not exploit any MCDMs or meta-heuristic algorithms and only uses two criteria of RE and distance to construct the uneven cluster-based routing tree for data gathering, thus having the lowest SDPR.

Table 10. Successfully delivered packet rate

Number of sensor nodes⇨Protocol⇩	100	150	200	250	300
FVT-EPO-UCR	0.953	0.931	0.902	0.851	0.810
FMCB-ER	0.932	0.890	0.869	0.831	0.789
UCFIA	0.890	0.841	0.795	0.772	0.721
UCR	0.778	0.752	0.730	0.691	0.623

5.2.4. Network lifetime

Figure 6 and Table 11 show the simulation results of network lifetime. From the simulation results, it can be seen that the proposed protocol has the longest network lifetime under all the number of SNs. If the number of SNs is 300, network lifetime of the proposed protocol is increased by 158.0%, 119.3%, and 113.7% compared to UCR, UCFIA, and FMCB-ER, respectively. Since the proposed protocol has the smallest REV, it is not without reason that it has the longest network lifetime. FMCB-ER comes the next and is superior to the other compared protocols for all cases of the number of SNs. This indubitably indicates that when the integrated FAHP-TOPSIS and EPO are applied to the cluster-route establishment phase of the cluster-based routing protocol, it predominates over the other protocols. The next order is UCFIA. UCFIA protocol uses fuzzy logic and the max-min ACO to choose the CH nodes and to construct the routes to BS, thus indicating longer network lifetime compared to UCR.

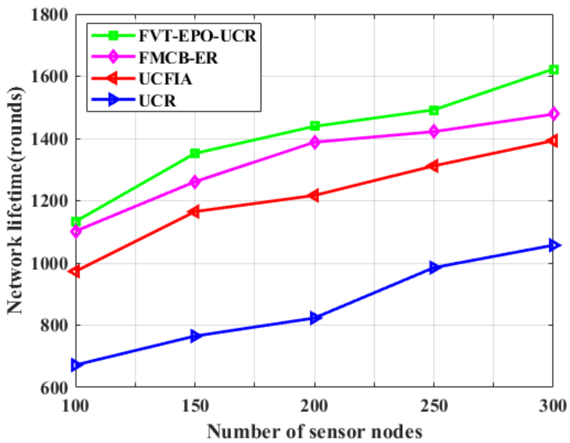

Figure 6. Comparison of network lifetime with varying the number of SNs

Table 11. Network lifetime (rounds)

Number of sensor nodes⇨Protocol⇩	100	150	200	250	300
FVT-EPO-UCR	1133	1352	1459	1492	1623
FMCB-ER	1102	1261	1388	1422	1478
UCFIA	973	1165	1217	1312	1393
UCR	672	765	823	985	1057

UCR has the lowest network lifetime. It is because this protocol does not use not only any MCDM or fuzzy logic to select the CH node, but also any meta-heuristics such as EPO or max-min ACO to construct a routing tree. As a result, this protocol consumes more energy and arises bigger REV, thus decreasing network lifetime. The simulation results related to the number of dead nodes when varying the number of rounds are shown in Figure 7 and Table 12. In this simulation, the number of SNs is fixed as 300.

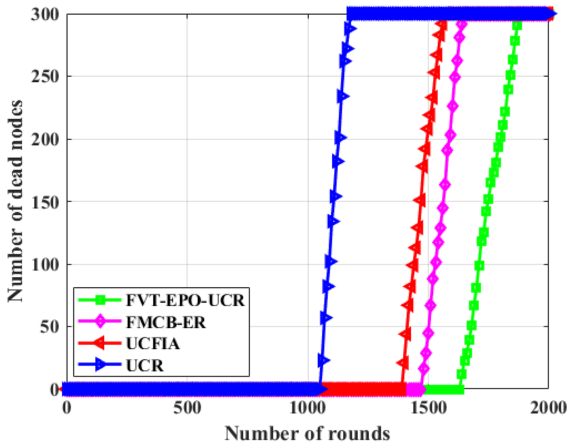

Figure 7. Comparison of the number of deads nodes in terms of the number of rounds

The number of dead nodes can be defined as the number of rounds till the first node dies (FND), one till the half of nodes in the network die (HND) and one till the last node dies (LND), respectively. When the number of SNs is 300, the number of rounds in terms of FND are 1043, 1381, 1449, and 1648 rounds for four compared protocols, that is, UCR, UCFIA, FMCB-ER, and FVT-EPO-UCR, respectively. FND, HND, and LND of the proposed protocol are 1648, 1746, and 1864 rounds, respectively, and they are much longer than FND, HND, and LND of the compared protocols. On the whole, we can conclude that the proposed protocol is absolutely superior to the other existing uneven cluster-based routing protocols in terms of the above four metrics.

Table 12. Number of dead nodes

Number of rounds⇨Protocol⇩	1000	1125	1250	1375	1500	1625	1750	1875	2000
FVT-EPO-UCR	0	0	0	0	0	0	152	300	300
FMCB-ER	0	0	0	0	45	272	300	300	300
UCFIA	0	0	0	0	208	300	300	300	300
UCR	0	191	300	300	300	300	300	300	300

6. CONCLUSION

A novel uneven cluster-based routing protocol proposed in this paper uses two integrated intelligent optimization methods, FCNP-VWA-TOPSIS and FCNP-VWA-EPO. An integrated FCNP-VWA-TOPSIS predominates over the individual MCDM methods or other integrated MCDM methods such as AHP-TOPSIS and FAHP-VWA-TOPSIS. The improved EPO blended FCNP-VWA to the traditional EPO i.e., an integrated FCNP-VWA-EPO is more predominant than existing protocols exploiting EPO and FAHP-TOPSIS-EPO. Thus, compared to existing protocols, the proposed protocol can maintain the stable operation of network, reliable transmission and good connectivity between the neighboring nodes in the whole network. In particular, the proposed protocol achieves smaller REV of 44.1%, 65.2%, and 88.2% compared to UCR, UCFIA, and FMCB-ER, respectively, thus prolonging the network lifetime greatly. The idea of optimal design which combines an integrated FCNP-VWA-TOPSIS with a meta-heuristic algorithm can be effectively applied not only in developing the cluster-based routing protocol for WSNs, but also in other branches such as designing the joint charging and data gathering protocol for WRSNs. We will try to improve the performance of the proposed protocol by combining an integrated FCNP-VWA-TOPSIS with other meta-heuristic algorithms superior to EPO and to extend the design idea of this paper to other fields in our future works.

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AUTHOR CONTRIBUTIONS STATEMENT

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

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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.

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