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MACR: A Novel Meta-Heuristic Approach to Optimize Clustering and Routing in IoT-based WSN

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Abstract: The primary focus in designing wireless sensor networks lies in optimizing energy efficiency, particularly through the implementation of routing and clustering techniques. This study aims to present cluster routing protocols that effectively conserve energy in wireless sensor networks. At the outset, we employed the Honey Badger Algorithm to select cluster heads. Using this technique, we can select the most effective cluster head from among all the sensors by taking into account things like residual energy and node proximity. The communication routing between base stations and cluster heads is accomplished using the African buffalo optimization technique. Parameters such as residual energy and node degree are utilized to determine the shortest path from source to destination. The proposed model's validity can be confirmed through a series of simulations as part of the experimental verification process. Comparing the suggested MACR protocol with Low energy adaptive clustering hierarchy(LEACH), Hybrid Energy Efficient Distributed(HEED), Fuzzy Reinforcement Learning based Data Gathering(FRLDG), and Fuzzy rule-based Energy Efficient Clustering and Immune-Inspired Routing(FEEC-IIR), in terms of network lifetime, packet delivery ratio, throughput, and end-to-end delay, the results show that the proposed protocol performs. and the consumption of energy.

Keywords: *wireless sensor network, clustering, routing, energy conservation, internet of things*

1. Introduction

The Wireless Sensor Network (WSN) is a network of small autonomous devices known as sensor nodes that collaborate to convey information about detected events to the base station [1]. WSN node deployment has the flexibility to be either deterministic or random [2]. The nodes are placed in a deterministic random pattern in inaccessible locations. Nodes collect data and then transmit it to a Base Station (BS) for processing [3]. Data can be transferred by using a single-hop or multi-hop communication [4]. Fig 1 depicts the single-hop and multi-hop methods. There are four primary components of a sensor node: a processing unit, a sensing unit, a communication unit, and a power supply [5]. Fig 2 represents the components of the sensor. In addition, the device receives the energy it needs from a power source to carry out its intended function. This power supply frequently contains a battery with a limited quantity of energy. Additionally, because nodes may be installed in an unfriendly or impossible location, charging the battery can be impossible or difficult. On the other hand, the sensor network needs to have a lifespan long enough to meet the needs of the application

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Generally, a sensor node loses its energy while sending and receiving data, compared with the sensing and processing unit. The first ordered Radio model is used for transmitting and receiving messages in WSN [6]. A sensor node's radio is ON when it is ready to either send or receive packets. This is known as Idle Listening.

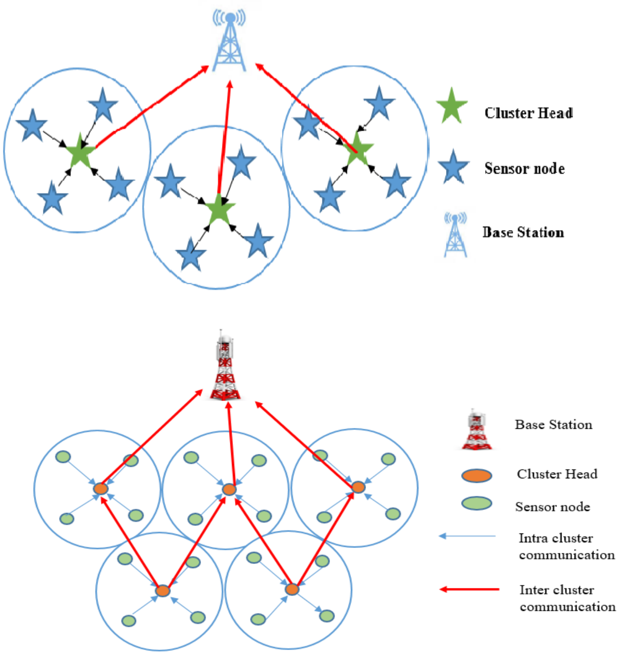

Fig 1: Single-hop and multi-hop communication

The major applications of WSNs include monitoring forest fires [7-8], military [9], healthcare [10-11], agriculture [12-13], and smart cities [14-15]. Scalability, fault tolerance, cost, reliability, hardware constraints, the WSN topology, the communication environment, and energy ingesting are all crucial considerations in WSN design [16-17].

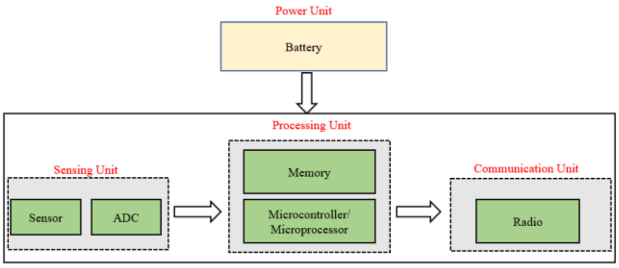

Fig 2: components of sensors

WSN lifetime might be improved by using clustering or routing [18]. Clustering is the process of grouping sensors into subcategories, or clusters, based on the characteristics each has. It is necessary to choose an extremely qualified node from inside an individual cluster to serve as the Cluster Head (CH). The function of the CH is to gather the data that has been sent in by the members of the cluster and send it either to a BS or a CH of a higher level, depending on the kind of transmission being used. In single-hop transmission, the CH directly transfers data to BS. In multi-hop transmission, the CH transmits the received data to a higher-level CH, who then passes it to the BS. Typically, the cluster members can be categorized into two groups: one comprising nodes with shared connections, and the other consisting of CHs.

Some approaches for clustering are present including hierarchical clustering [19], grid-based clustering [20], partition-based clustering [21], density-based clustering [22], and spectral clustering and Hierarchical clustering, which frequently employs greedy methods and stepwise optimization, frequently employs a tree structure. Hierarchical clustering can take either a top-down or bottom-up strategy. Data clustering using a grid layout to place sensor nodes in cells according to their physical location or proximity is called grid-based clustering in WSNs. In WSNs, partition-based clustering is a data clustering technique that aims to divide network nodes into non-overlapping partitions or clusters according to their similarities or dissimilarities in data measurements or other properties. In WSN, data clustering using the density of neighbouring nodes is called density-based clustering. In WSNs, spectral clustering is a data clustering method that uses spectral graph theory to divide sensor nodes into groups based on how similar or different their data readings are or how they are different in other ways.

The routing process aims to identify the path that will result in the least amount of energy consumption, the longest lifespan for the network, and the most reliable and timely transmission of data. Energy constraint, network dynamics, data aggregation, and data transfer are the four most critical elements that have an impact on routing. The necessity to conserve energy affects both multi-hop and single-hop transmission techniques. The multi-hop method reduces both power usage and transmission distance. There are three different types of data transport models: event-driven [23], time-driven [24], and query-driven [25]. When an event occurs, the nodes report in an event-driven model. Each node in the network sends and receives data at regular intervals in the time-driven model. The BS establishes connectivity in the query-driven model by sending a request, to which the nodes reply.

The following key points are contributions of my work

- The focus of this study is on establishing an energy-efficient WSN routing technique related to clusters, with metaheuristics serving as the primary design approach.
- This research presents the MARC method, which aims to increase the WSN's energy efficiency and longevity through the use of refined clustering and routing procedures.
- The suggested model requires that the target area be partitioned into somewhat uniformly sized grid cells. The BS uses HBO within each grid to choose who the CH will be
- The communication routing between base stations and cluster heads is accomplished using the ABO technique
- The results section demonstrates a comparison between the efficiency of the MACR protocol and several other widely used low-power protocols. The findings indicate that the suggested MACR protocol surpasses LEACH, HEED, FRLDG, and FEEC-IIR in various key performance metrics, including network lifetime, packet delivery ratio, throughput, end-to-end delay, and energy consumption

The remaining paper is structured as follows:

Section 2 presents an extensive survey of pertinent publications, while Section 3 details the proposed MARC protocol. The simulation results are displayed in Section 4, followed by a summary of the work in Section 5.

2. Related Work

The architects of LEACH [26] created a protocol architecture that combines application-aware data aggregation with energy-efficient cluster-based routing and media access. The goals of this architecture are to lengthen the lifespan of the system, decrease latency, and boost the quality that applications experience. LEACH employs algorithms for cluster adaptability and alternation of cluster heads to equalize energy consumption among nodes, distributed signal processing to preserve communication resources, and a distributed cluster formation method for the self-organization of many nodes. The experimental results show that LEACH works wonderfully despite the severe limitations of the wireless channel.

An ideal CH can be chosen from a pool of sensor nodes using the Mayfly algorithm, which was proposed in [27]. The appointment of the CH is based on the following criteria: residual energy, node density, neighbour distance, node level, and BS distance. The best candidate for CH is designated based on the above five criteria. From all of the sensors in the network, the one with the highest fitness according to MFA is selected as the CH. We have used residual energy and several distance characteristics, such as the average intra-cluster distance between the sensor nodes and their space from the Base station, to pick efficient CH with energy efficiency, as proposed in [28].

In [29], an ideal CH was chosen from a pool of nodes using the Butterfly Optimisation Algorithm (BOA). The CHs process was optimized based on several measures, including residual energy, neighbour distance, distance to BS, node centrality, and node degree. The Ant Colony Optimisation (ACO) technique was then used to find out the best way from the CH to the BS. This method determined the best route by factoring in energy, distance, and node degree.

In [30], an innovative approach to clustering and routing was introduced, primarily relying on Genetic Algorithms (GAs) and Equilibrium Optimization (EO) techniques. To enhance scalability, the sensor nodes were first clustered in the initial phase using GA, followed by the selection of optimal CHs. In the subsequent step, all nodes transmitted their collected data to the CHs. The key contribution of this research was the reduction of energy consumption in the WSN achieved by employing GA for clustering and EO techniques for selecting the ideal paths among the CHs and the BS.

Through its clustering and routing operations, the MHCRT-EEWSN [31] method introduced here aims to improve energy efficiency and extend the WSN's lifespan. To achieve effective clustering, this model employs the Whale Moth Flame Optimisation (WMO) technique, which uses a fitness function to optimize intra-cluster distance, inter-cluster distance, energy levels, and balancing variables. In addition, the Improved African Buffalo Optimisation (IABO) based routing technique is incorporated into the MHCRT-EEWSN model. This approach identifies the optimum routes inside the WSN by designing a fitness function to consider several factors, including residual energy and distance.

In [32], the author proposed a novel protocol called FEEC-IIR (Adaptive Fuzzy Rule-Based Energy Efficient Clustering and Immune-Inspired Routing) designed specifically for WSNs in IoT systems. In an adaptive fuzzy multi-criteria decision-making (AF-MCDM) protocol, CHs are chosen based on the energy status, the impact on QoS, and the location of the nodes. By employing cluster-based routing, the protocol effectively minimizes energy consumption. Additionally, to improve the reliability of data delivery, an immune-inspired optimization(IIM) algorithm is used for transmitting purposes.

Energy-aware adaptive fuzzy neuro clustering with the WSN-assisted Internet of Things (IoT) method EAANFC-MR is introduced in [32]. Clustering and multi-hop routing, both derived from the EAANFC method, make up the main part of the EAANFC-MR algorithm. To determine which nodes will act as CHs, the EAANFC-based cluster strategy takes into consideration parameters including Residual Energy, Distance, and Node Degrees. CHs are necessary for the network's organization and for collecting data from their associated nodes. The next stage is to use the QOBFO algorithm as a multi-hop Route Technique to determine the optimal paths to the destination.

In [33], the author presents an innovative approach that combines an energy-efficient opportunistic routing algorithm with fuzzy-based Grey Wolf Optimization (GWO). To conserve energy and ensure that nodes in a wireless sensor network all use about the same amount of power, an opportunistic routing strategy has been proposed. The selection of CH involves considering several factors, namely, residual energy, node centrality, and neighbourhood overlap. These criteria collectively determine the most suitable node to be designated as a CH.

In [34], the author presents an intelligent approach, called the Neuro Fuzzy Emperor Penguin Optimization (NF-EPO) approach, for designing energy-efficient trajectories in mobile sink-based IoT-supported Wireless Sensor Networks. The methodology begins by forming clusters using a grid concept and then employs a fuzzy-based cluster head selection method to identify the most suitable CH. The Adaptive Neuro-Fuzzy Inference System (ANFIS) achieves this by taking into account the nodes' residual energy, the nodes' neighbour counts, and the nodes' historical behaviours. The mobile sink's ideal route and Relay Points are then calculated using the Emperor Penguin Optimisation (EPO) method.

Table 1. represents an assessment of Recent Approaches

Ref No	CH selection		Routing		Limitations
	Optimization technique	Parameters	Optimization technique	Parameters	
[30]	WMO	energy levels, inter-cluster distance, intra-cluster distance, and balancing factors	IABO	residual energy and distance factors	May not be suitable for dynamic network scenarios.
[31]	AF-MCDM	QoS impact, node location, and energy status	immune-inspired optimization	Energy factor, Distance factor, Node density	Performance impact on large-scale networks
[32]	EAANFC	Residual Energy, Distance, and Node degrees	NA	Number of hops, Distance to destination, Link quality	Evaluation on various network scales may be missing
[33]	Fuzzy	Residual energy, Node centrality, Neighbor count	GWO	Number of hops, Energy consumed, Distance to the base station	Validation on real-world scenarios may be limited
[34]	ANFIS	historical behavior of nodes, number of neighbors around a node, residual energy.	EPO	Optimal travel path, Relay Points for mobile sink	Limited exploration of large-scale WSN environments.
[35]	Group Teaching Optimization	The energy of the node, no of neighbors, and intra-cluster distance.	Dear Hunting Optimization	Residual energy and distance factor.	May not be universally suitable for all categories of WSNs applications.
[36]	LEACH	Residual Energy	Improved Spider Money Optimization	Residual energy and distance	The paper does not explicitly mention any limitations of the proposed method.
[37]	Dragonfly Algorithm	node density, residual energy, distance, and intra-cluster communication	Global Search Optimization	inter-cluster distance	scalability of the proposed algorithm for larger networks.
[38]	Self-Organizing Map-based Firefly Algorithm	Distance and residual energy	improved Ant Colony Optimization	angle, distance, and energy of the node.	

3. Proposed Model:

In this study, we propose a novel approach for WSNs. The proposed MARC approach selects a CH at the root level by applying HBO, using fitness functions(FF) such as residual energy and node proximity. Route selection through the ABO algorithm follows cluster formation and CH selection. To finalize the optimal route from source to destination, the ABO algorithm considers factors like distance and remaining energy. The comprehensive operations of these procedures are elaborated below. Fig 3. Represents the strategy of the suggested MARC for WSNs and Fig.4 represents the optimization techniques and performance measures used in the proposed MARC.

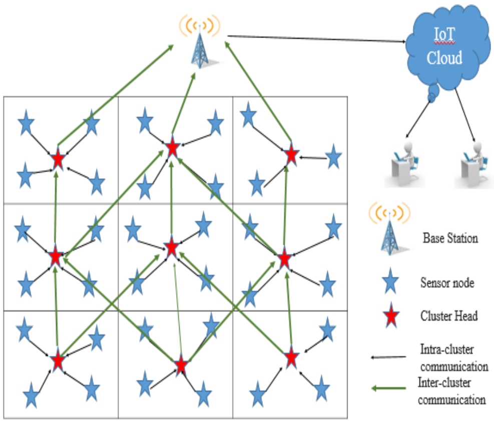

Fig. 3 Architecture of the proposed model

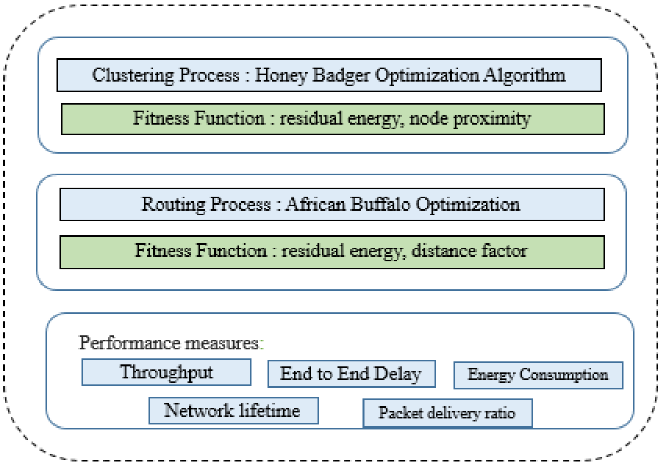

Fig. 4: Optimization techniques and performance measures of the proposed model

The suggested model divides the target area into n equal-sized grids. The system's sensor nodes maintain standardization, being equipped with both temperature sensors and Global Positioning Systems (GPS). These sensor nodes can be distributed arbitrarily throughout the intended landscape. By changing its broadcast power, each sensor node can transmit information directly to the BS. The BS, which separates the affected area, is aware of the grid's precise measurements. Periodically, the sensor nodes will transfer a packet of information to the BS.

The proposed model is structured into two distinct phases: (i) Setup and (ii) Steady-State. During setup, the BS selects CHs by applying HBO and then sets up multi-hop connections between them. This phase establishes the groundwork for the system's following steady-state operation.

Throughout the setup phase's initiation, every sensor node initiates an information message (SNinfo) transmission to the BS. The SNinfo message comprises three key components: SNuid, representing the sensor node's unique identifier; SNre, representing the node's residual energy; and SNgn, indicating the grid digit to which the node belongs. The BS applies HBO to select a CH in each grid. The fitness functions for selecting CHs are residual energy and node proximity. Fig 5 depicts the flow chart for the proposed MARC

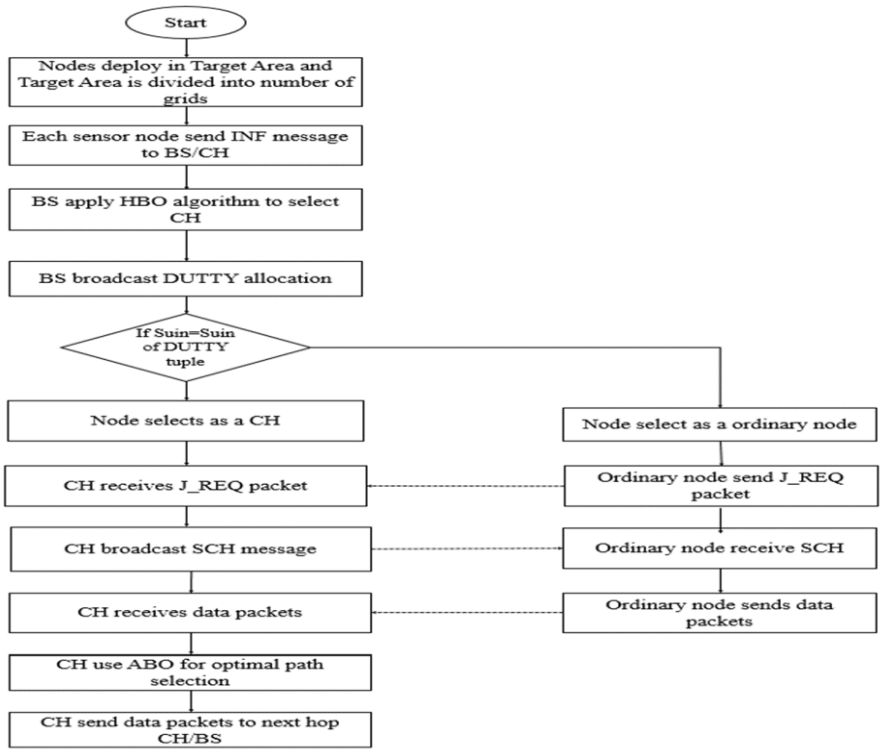

Fig.5 Flowchart for the proposed model

3.1 Honey Badger Optimization for CHs:

The HBO motivation is reserved for the thoughtful animal called the Badger in finding the prey has honey [39]. The modeling of new expression processing equations is inspired by the dynamic search behavior observed in honey badgers as they diligently explore and search for their valuable honey. The honey badger utilizes a unique rat sniffing approach, which involves a deliberate and repetitive exploration, enabling it to carefully search for potential prey and dig approximately 50 burrows within a radius exceeding 40 kilometers per day.

Honey badgers have a fondness for honey, although they struggle to find beehives on their own. To overcome this challenge, they form a symbiotic partnership with birds. The bird guides the badger to the beehives, and with its long claws, the bird assists in opening the hives. Through this teamwork, both the bird and the badger reap the benefits of accessing the honey. Mathematically, the steps of the proposed HBA can be outlined as follows. The HBO algorithm's flowchart is shown in Fig 5.

Set the population size N and initialize the positions of the honey badgers accordingly, using Equ.1

$$x_n = lb_n + r \times \left(ub_n - lb_n\right) \quad (1)$$

The above equation x_n signifies the position of the nth honey badger, which corresponds to a potential solution in the population of honey badgers. The variables lb_n ub_n denote the lesser and greater bounds of the search domain, correspondingly. r is a random number.

The honey badger's ability to smell its prey depends on both the strength of its focus and the proximity of the prey to the animal.

$$I_n = r1 \times \frac{S}{4\pi d_n^2} \quad (2)$$

$$S = \left(x_n - x_{n+1}\right) \quad (3)$$

$$d_n = x_{prey} - x_n \quad (4)$$

The term S is used to describe the intensity or potency of a source. d_n signifies the space between the prey and the nth honey badger. The prey's intensity strength is represented by I_n. Here, x_{prey} denotes the prey's location, analogous to the optimal individual's position within the algorithm. r1 denotes the random number.

As the number of repetitions rises, the rate of density factor reduction gradually slows down, ensuring a smooth transition from exploration to development. The diminishing factor is continuously updated throughout iterations to minimize the level of randomization, represented mathematically as follows

$$\alpha = k \times \exp\left(\frac{-t}{t_{\max}}\right) \quad (5)$$

In this context, k represents a constant that is equivalent to or more than 1, with the default value set at 2. The variable t signifies the present number of iterations, whereas t_{max} represents the maximum number of iterations.

The mining stage involves the process in which honey badgers search for prey, as depicted by the following expression

$$x_{new} = x_{prey} + A \times \delta \times I \times x_{prey} + A \times r_2 \times \alpha \times |\cos(2\pi r_3) \times (1 - \cos(2\pi r_4))| \quad (6)$$

In this context, x_{new} signifies the honey badger's revised location, while α representing the distance separating the nth honey badger from the prey. x_{prey} represents the best prey location, δ (greater than or equal to 1) signifies the honey badgers' ability to acquire food and α represents the distance between the prey and the n-th honey badger. Additionally, r2, r3, and r4 are three distinct random numbers ranging from 0 to 1. I which denotes the intensity of prey odor, and A is utilized as the agent's search direction to ensure a strict change in search direction.

In the honey stage, the second location update process involves the cooperation between honeyguide birds, showcasing their inherent mutual beneficial relationship. The honeyguide actively searches for hives in various locations and, upon discovering the hive's location, emits a harsh scream. The updated expression for this stage is as follows:

$$x_{new} = x_{prey} + F \times r_5 \times \alpha \times d_n \quad (7)$$

x_{new} designates the honey badger's fresh position, Meanwhile, x_{prey} signifies the prey's position, F and α, along with d_n, are metrics computed during the update process of honey badger searches near the x_{prey} location. r_5 is a random number.

HBO algorithm uses the following parameters for fitness functions to choose CH from every grid.

The word "residual energy" is used to describe the amount of power still available in a sensor node after it has been used for some time in a WSN. The following equation is used for calculating residual energy.

$$f1(E_r) = E_i - E_s \quad (8)$$

$$E_s = E_{rec} + E_{tran} + E_{idle} \quad (9)$$

Here, E_r denotes residual energy of node, E_i denotes node initial energy and E_s represents node spending energy. E_{rec} denotes receiving energy, E_{tran} energy spent on transmission data and E_{idle} energy spent while the node remains ideal.

Using their coordinates in the same coordinate system, a WSN's proximity function may calculate the distance between any two nodes. The following formula is used to determine the distance between any two nodes:

$$f2(D) = ((x_2 - x_1)^2 + (y_2 - y_1)^2)^{\frac{1}{2}} \quad (10)$$

Here, D= distance between the two nodes

x_1, y_1 are the coordinates of the first node

x_2, y_2 are the coordinates of the second node

The below equation is used to calculate the fitness function

$$f = (f1(E_r) \times 0.7) + (f2(\mathrm{D}) \times 0.3) \quad (11)$$

The following algorithm represents the HBO

Algorithm1:Pseudocode code for HBO

Step 1: Set the parameters tmax, N, β, and C.

Step 2: Generate an initial population of N honey badgers with random positions within the solution space.

Step 3: calculate the fitness value of each honey badger's position (xi) using the objective function and store it in fi, where i ∈ [1, 2, ..., N].

Step 4: Save the position of the honey badger with the best fitness value (xprey) and assign its fitness value to fprey.

Step 5: while until t ≤ tmax do

Step 6: Update the value of the decreasing factor α using a specific Eq. (5)

Step 7 : for i = 1 to N do

Step 8: Calculate the intensity (Ii) of the honey badger by using Eq. (2)

Step 9: if r < 0.5 then r is a random number between 0 and 1

Step 10: Update the position xnew using Eq. (6). else

Step 11: Update the position xnew using Eq. (7).

Step 12: If the new fitness value (fnew) is less than or equal to the best fitness value (fprey), update the best position (xprey) and best fitness value (fprey).

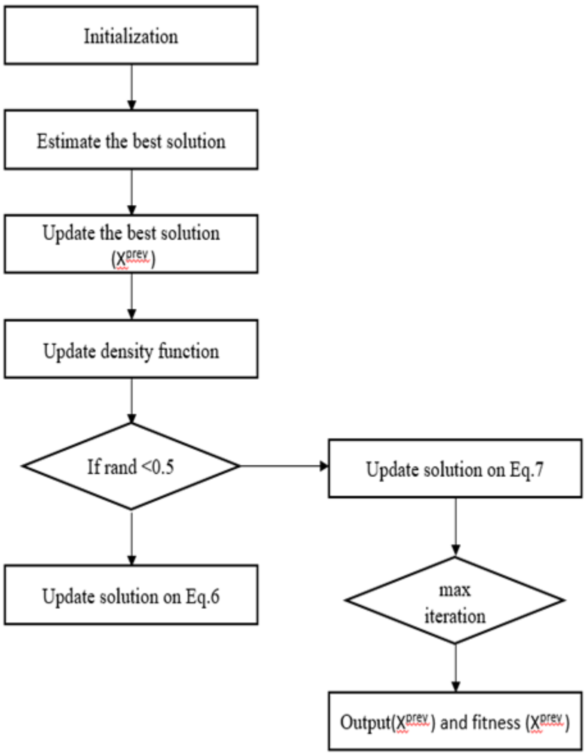

Fig. 6 Flow chart for HBO

After selecting CHs in each grid, the BS informs about selected CHs by broadcasting DUTTY allocation. The DUTTY allocation tuple contains SN_{uid} and SN_{gn}. If the SN_{uid} of a sensor node matches its SN_{uid} in any tuple then the node itself has been selected as a CH for the current round. Each ordinary node initiates a join request (J_REQ) message to its respective CH. The ordinary node identifies its CH based on the matching grid number between the CH and the node itself. The J_REQ message carries the SNuid and SNgn of the requesting node. the CH accepts all the requesting nodes as members of its cluster. Following a predefined time-out period, the BS broadcasts a message to inform CHs in the target area about the frame size and structure. Each CH broadcasts an intra-cluster schedule CH_{sch} within its cluster. The CHsch tuple contain SN_{uid} and SN_{slot} . The CH gathers the information from the member node and finds the optimal path from source to destination by applying African Buffalo Optimization(ABO) Algorithm. Fig 7 represents the overall process of the proposed architecture.

3.2 African Buffalo Optimization for Routing

Once the cluster is formed and CHs are selected, the next step is the route selection using the ABO algorithm. ABO is an innovative metaheuristic technique that takes ideas from herd management and efficient migratory communication

[40]. They use the vocalizations "waaa" and "maaa" to exploit and explore the environment during the migration. The "waaa" sound is used to move to a new location since the current location might not have sufficient pasture, whereas the "maaa" sound calls the buffalo to stay in its current location, which has ample pasture and is safe. How this noise helps in the quest for food can be expressed quantitatively by the following equation.

$$m_{n+1} = m_n + lp^1(b_{\max} - w_n) + lp^2(b_{\max.n} - w_n) \quad (12)$$

Here, m_n represents the sound "maaa" with a specific association with a buffalo's call (n = 1, 2, ..., k). $b_{\max}$ indicates the buffalo's best position within the herd, and $b_{\max.n}$ represents the optimal position discovered by buffalo k. lp^1 and lp^2 refer to learning parameters in the range of [0, 1]. m_{n+1} denotes the relocation of a buffalo from its current position m_n to a novel position, reflecting the buffalo's wide memory capability in its migration lifestyle. The relocation is defined as follows

$$w_{n+1} = \frac{w_n + m_n}{\lambda} \quad (13)$$

In Equation 13, w_{n+1} represents the transition to a new position, while w_n signifies the current exploration value associated with the sound "waaa" and m_n denotes the current exploitation value. The variable "1" determines the time interval for the buffalo's movement, and it is typically fixed at 1

The following algorithm outlines the ABO approach through the random insertion of the n[th] buffalo. The achieved optimal solution relies on modifying the buffalo's movements. During every iteration, the fitness value attained is compared, and the best among all individuals is assigned to "bgmax" (best global position), while the best for each buffalo is allocated to "bgmax.n" (best local position). Every buffalo updates its position and movement based on the best adjacent buffalo, allowing them to move towards the optimal solution and track it effectively. Fig 6 denotes the flowchart for ABO.

The objective of this procedure was to identify the optimal set of routes from multiple nodes in CH to the BS using an FF that considers two parameters: distance and energy. Initially, the Residual Energy(RE) of the next-hop node was defined, and the node with the highest energy level was selected as the Relay Node. Consequently, the node with a greater RE value would serve as the next-hop node in the routing process, determined as follows:

$$f1 = E_{ch} \quad (14)$$

Furthermore, the Euclidean distance can be utilized to define the distance from CH to BS. Opting for the shortest distance helps to keep energy consumption significantly lower. As the distance increases, additional energy is expended. Consequently, the node with the minimum distance is favored as the optimal route.

$$f2 = \frac{1}{\sum_{i=1}^{m} dist(CH_i, NCH) + dist(NCH, \mathrm{BS})} \quad (15)$$

Here, CH_i represents the ith CH, NCH denotes the next CH. The sub-objective mentioned above is regarded as the FF, where α_1 and α_2 represent the weights assigned to each sub-objective.

$$Fiteness = \alpha_1(f1) + \alpha_2(f2)$$
$$Where \quad \alpha_1 + \alpha_2 = 1, \alpha_i \in (0,1) \quad (16)$$

The below algorithm depicts the pseudocode for ABO and Figure.7 represents the flowchart.

Algorithm 2: Pseudocode code for ABO
Step 1: Initialization Initialize nth buffalos randomly on the target area Step 2: Analysis of buffalo fitness value and allocating the best bgmax individual buffalo best bgmax.n Step 3: update the buffalo fitness values based on Euq.12 Step 4: update the moment of the buffalo based on Equ.13 Step5: is bgmax upgrading then goto step 6 else goto step 1 Step6: check the validation of the ending condition, where it meets or else goto step 7 , no goto step: 2 Step 7: return the optimal solution

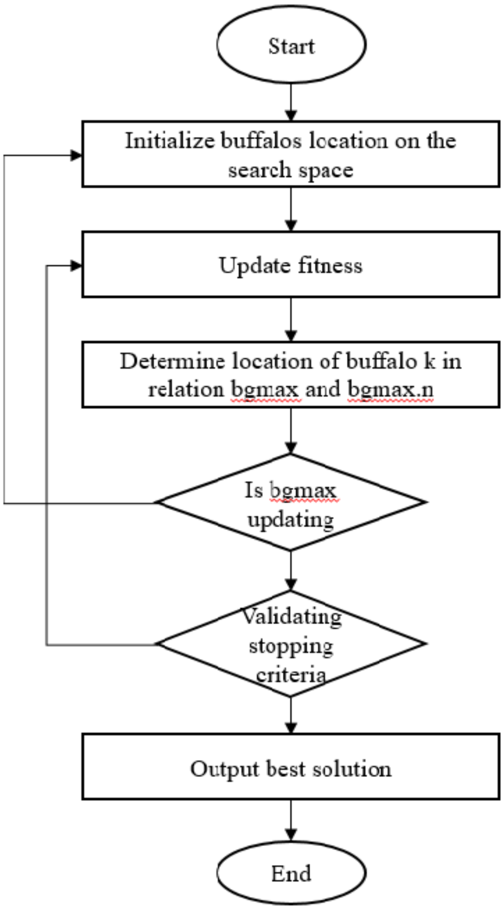

Fig.7: Flow chart for ABO

4. Result Analysis

In this section, we perform an in-depth assessment of the model involving different numbers of sensor nodes. Table 2 contains the parameters utilized in the simulations. In this context, "E_{lec}" signifies the power consumption for operating the circuitry of a transmitter or receiver. The term "E_{idle}" signifies the energy expended during idle mode. Additionally, the symbol "E_{amp}" denotes the power utilized by the transmit amplifier.

Table 2: Simulation Parameters.

Parameter	Value
Eidle	40 nJ/bit
Eamp	100 pJ/bit/m2
Target Area	100 × 100 m2 / 50 × 50 m2
Control packet size	20 bytes
Quantity of Nodes	100/200/300/400/500
Number of cluster heads	16
Eelec	50 nJ/bit
Data/schedule packet size	100 bytes

4.1 Result Analysis of Throughput

Table 3 and Figure 8 show a complete examination of the throughput for the proposed MARC model and a few existing approaches, taking into account various node scenarios. The experimental results specify that the MARC model has exposed superior performance, achieving maximum throughput values across all Sensor Nodes. As an illustration, when considering 100 SNs, the MARC approach achieved a higher throughput of 0.99 bps, while the LEACH, HEED, FRLDG, and FEEC-IIR models validated lower throughputs of 0.65 bps, 0.74 bps, 0.89 bps, and 0.95 bps, respectively.

Table 3: Throughput analysis of MARC with existing protocols

Method/no of nodes	100	200	300	400	500
LEACH	0.65	0.62	0.51	0.45	0.36
HEED	0.74	0.65	0.57	0.51	0.41
FRLDG	0.89	0.79	0.74	0.64	0.54
FEEC-IIR	0.95	0.82	0.72	0.68	0.60
Proposed	0.99	0.93	0.87	0.81	0.74

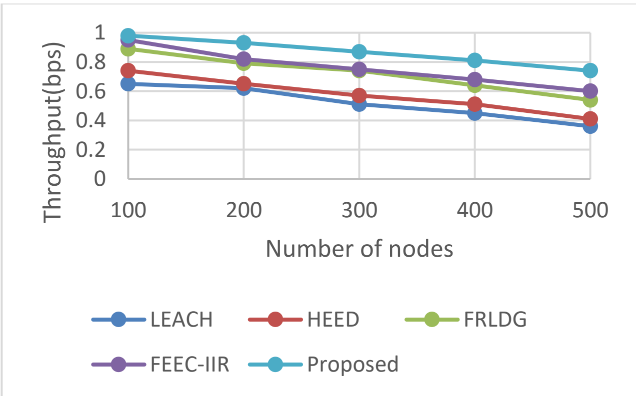

Fig.8: Throughput analysis of MARC approach under distinct nodes

4.2 Result analysis of End-to-End delay

Table. 4 and Fig 9 present a detailed analysis of the End-to-End Delay (ETED) for the proposed MARC model and various existing techniques, considering diverse node scenarios. For example, when considering 100 and SNs, the MARC model performs better results with a minimal ETED of 2.01 ms. In contrast, the LEACH, HEED, FRLDG, and FEEC-IIR models obtained maximum ETED values of 6.15 ms, 5.18 ms, 3.39 ms, and 2.2 ms, respectively. The MARC model performs better results with 100 and 200 SNs, for 300, 400, and 500 SNs it performs better result than LEACH, HEED, and FRLDG.

Table 4: End-to-end delay analysis of MARC with existing protocols

Method/no of nodes	100	200	300	400	500
LEACH	6.15	6.85	8.02	9.47	9.86
HEED	5.18	5.80	7.13	9.00	9.31
FRLDG	3.39	4.48	5.33	7.32	8.69
FEEC-IIR	2.2	2.35	4.25	5.5	6.10
Proposed	2.01	2.3	4.3	5.08	6.25

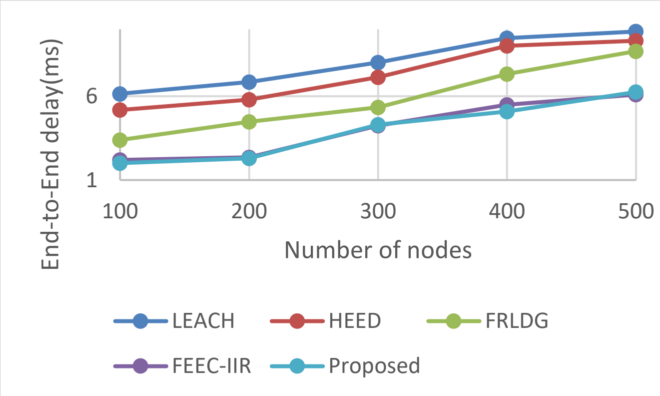

Fig.9: EDED analysis of MARC methodology under distinct nodes

4.3 Result Analysis of Energy Consumption

Table 5 and Fig.10 provide an analysis of the Energy Consumption(EC) for the projected MARC and various existing techniques. For example, when considering 100 SNs, the MARC model achieved highly efficient results with a minimal EC of 38.74 mJ. In contrast, the LEACH, HEED, FRLDG, and FEEC-IIR models obtained maximum EC values of 151.16 mJ, 122.20 mJ, 51.42 mJ, and 45.15 mJ, respectively

Table 5: Energy Consumption analysis of MARC with existing **protocols**

Method/no of nodes	100	200	300	400	500
LEACH	151.16	171.27	181.73	205.06	242.86
HEED	122.20	149.55	170.47	188.97	227.58
FRLDG	51.42	69.92	103.70	140.71	169.66
FEEC-IIR	45.15	60.50	95.25	110.15	150.55
Proposed	38.74	54.78	76.27	115.75	146.75

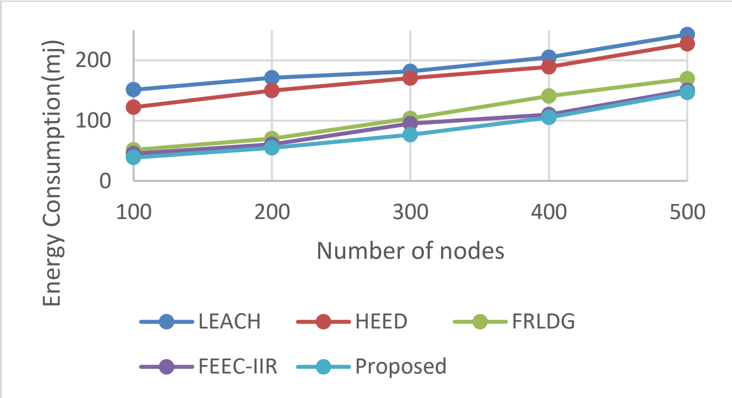

Fig.10: EC analysis of MARC approach under distinct nodes

4.4 Result Examination of Packet Delivery Ratio

Table 6 and Fig. 11 offer an analysis of the Packet Delivery Ratio (PDR) for the suggested MARC model and various present techniques. The experimental results indicate that the MARC model has shown superior performance, achieving maximum PDR values across all SN. For instance, when considering 100 SNs, the MARC model exhibited a higher PDR of 99.50%, while the LEACH, HEED, FRLDG, and FEEC-IIR models demonstrated lower PDR values of 92.81%, 94.82%, 98.14%, and 99.00%, respectively. The proposed model is not performing better results compared then FEEC-IIR with 300/400/500 SNs.

Table 6: Packet Delivery Ratio analysis of MARC with present protocols

Method/no of nodes	100	200	300	400	500
LEACH	92.81	90.81	88.95	86.87	84.78
HEED	94.81	93.74	91.50	89.96	88.80
FRLDG	98.14	97.45	95.44	94.28	93.74
FEEC-IIR	99.00	98.05	97.00	96.00	95.25
Proposed	99.5	98.72	96.5	95.25	94.75

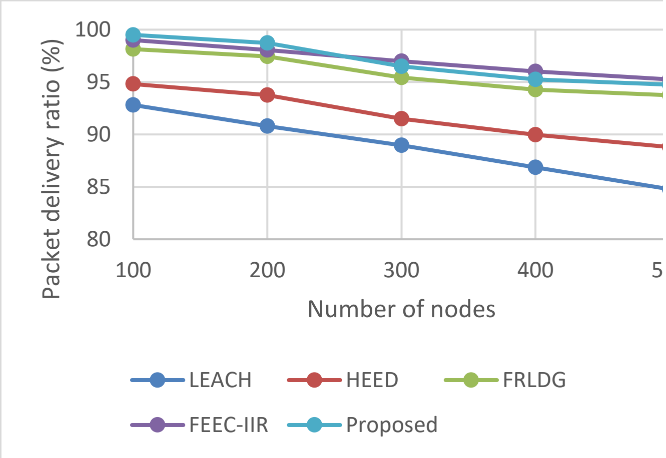

Fig.11: PDR analysis of MARC approach under distinct nodes

4.5 Evaluation of Network Lifespan Results

The comprehensive examination of the Network period for the proposed MARC model, along with the latest methods, is presented in Table 7 and Fig. 12. The simulation results indicate that the MARC model has demonstrated superior performance, achieving maximum Network Lifetime values across all SN. In the case of 100 SNs, the MARC approach showed a higher Network Lifetime of 5542 rounds, whereas the LEACH, HEED, FRLDG, and FEEC-IIR models exhibited lower Network lifetime values of 4498, 4689, 5169, and 5500 rounds, respectively.

Table 7: Network Lifetime analysis of MARC with present protocols

Method/no of nodes	100	200	300	400	500
LEACH	4498	4239	3990	3140	3081
HEED	4689	4505	4254	4048	3723
FRLDG	5169	4933	4689	4512	4321
FEEC-IIR	5500	5200	5000	4900	4700
Proposed	5542	5261	5217	5107	5024

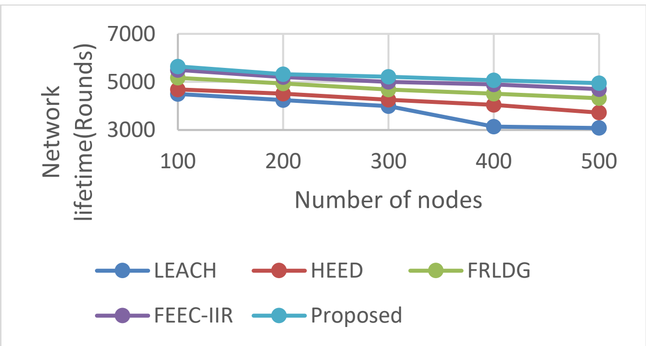

Fig.12: Network Lifetime analysis of MARC approach under distinct nodes

Table 8 represents the analysis of various WSN protocols, evaluating their performance characteristics across different metrics. The protocols listed LEACH, HEED, FRLDG, FEEC-IIR, and Proposed-MACR are being assessed based on the specified criteria Throughput, ETED, EC, PDR, and Network Lifetime, each categorized into High, Medium, and Low based on performance levels.

Table 8: Comparison table

	Throughput			ETED			EC			PDR			Network Lifetime		
	H	M	L	H	M	L	H	M	L	H	M	L	H	M	L
LEACH	✔			✔			✔			✔			✔		
HEED	✔			✔			✔			✔			✔		
FRLDG		✔			✔			✔			✔			✔	
FEEC-IIR			✔			✔			✔			✔			✔
Proposed-MACR			✔			✔			✔			✔			✔

H- High, M-medium, L-low

5. Conclusion

This framework presents a novel MARC algorithm tailored for WSNs. At the primary level, the MARC model utilizes the HBO algorithm to select CHs established on a fitness function energy, and node proximity. The ABO algorithm is used for route selection since it creates a fitness function using several factors, such as residual energy and distance factor. The proposed system enhances the reliability of link data collection nodes and improves service metrics, including throughput, end-to-end delay, Energy Consumption, PDR, and Network lifetime. Comparing the suggested MARC protocol with LEACH, HEED, FRLDG, and FEEC-IIR, the results demonstrate that the suggested protocol outstrips in terms of throughput, packet delivery ratio, end-to-end delay, and network lifetime.

Author contributions

Ramesh Babu Pedditi: Conceptualization, Methodology, Software, Field study **Ramesh Babu Pedditi:** Data curation, Writing-Original draft preparation, Software, Validation., Field study **Kumar Debasis:** Visualization, Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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