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Hybridization of Metaheuristic Algorithm for Dynamic Cluster-Based Routing Protocol in Wireless Sensor Networks

SHAHA AL-OTAIBI[1], AMAL AL-RASHEED[1], ROMANY F. MANSOUR[2], EUNMOK YANG[3], GYANENDRA PRASAD JOSHI[4], AND WOONG CHO[5], (Member, IEEE)

[1]Information Systems Department, College of Computer and Information Sciences, Princess Nourah Bint Abdulrahman University, Riyadh 11564, Saudi Arabia
[2]Department of Mathematics, Faculty of Science, New Valley University, El-Kharga 72511, Egypt
[3]Department of Financial Information Security, Kookmin University, Seoul 02707, South Korea
[4]Department of Computer Science and Engineering, Sejong University, Seoul 05006, South Korea
[5]Department of Automotive ICT Convergence Engineering, Daegu Catholic University, Gyeongsan 38430, South Korea

Corresponding authors: Gyanendra Prasad Joshi (joshi@sejong.ac.kr) and Woong Cho (wcho@cu.ac.kr)

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ABSTRACT Energy efficiency is considered the major design issue in wireless sensor networks (WSN), which can be addressed using clustering and routing techniques. They are treated as Non-deterministic Polynomial (NP)-hard optimization problems and are solved using metaheuristic algorithms to identify the optimal or near-optimal solutions. With this motivation, this paper develops a hybridization of the metaheuristic cluster-based routing (HMBCR) technique for WSN. The HMBCR technique initially involves a brainstorm optimization with levy distribution (BSO-LD) based clustering process using a fitness function incorporating four parameters such as energy, distance to neighbors, distance to the base station, and network load. Besides, a water wave optimization with a hill-climbing (WWO-HC) based routing process is carried out for optimal route selection. Extensive experimentation analysis is performed to ensure the energy efficiency and network lifetime performance of the HMBCR technique. The experimental outcome ensured the superior results of the HMBCR technique over the compared methods under different aspects.

INDEX TERMS Clustering, energy efficiency, metaheuristics, routing, WSN.

I. INTRODUCTION

Generally, wireless sensor networks (WSN) are defined as an infrastructure-less system with minimum cost sensor nodes (SN) to observe the climatic conditions. A massive number of SNs were placed randomly in a location to sense the concerned platform. Also, WSN plays a significant role in monitoring the atmospheric state like climate inclination, forest-fire existence, farming, medical science, disaster control, border observation, smart cities, and so on [1]. Practically, it is employed for observing diverse attributes like temperature, humidity, moisture content, gas, acoustics, vibrations, and so forth. An SN is manufactured with numerous sensors, microcontroller, communication unit as well as power supply. The major responsibility of the sensor unit is to monitor the atmosphere, collect the data, and forward them to adjacent SN through a communication unit [2]. But the nodes have limited energy, bandwidth, storage space, and processing ability. Moreover, there are other common problems like security, fault tolerance, connectivity, coverage, synchronization, scheduling, and localization issues. On many cases, SN are deployed in unattended or harsh regions where the batteries cannot be replaced or recharged [3]. Unfortunately, communication cost is more expensive when compared with sensing as well as processing cost. As the node has limited energy and remains non-replaceable, available node energy has to be consumed effectively. Among all other features of WSN, power efficiency is one of the major causes that affect the entire network performance. Hence, manufacturing components of WSN protocols have to be elegant, energy-effective, and adaptable to different ecological states.

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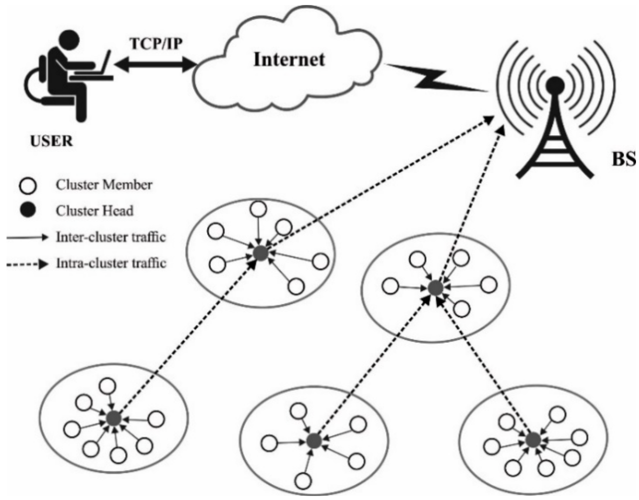

FIGURE 1. The clustering process in WSN.

Different types of clustering and routing protocols with diverse factors were deployed for developing energy-effective WSN [4]. Among massive algorithms, clustering is a well-known and remarkable approach that classifies the network and collects the adjacent nodes as clusters. A dominant node called Cluster Head (CH) would be elected from alternate nodes, whereas the remaining nodes are termed as Cluster Members (CMs). The tasks of making clusters with an equal number of nodes in a system are named Equal Clustering, while unequal numbers of nodes are referred to as Unequal Clustering. From all clusters, a CH is elected according to the specific criteria. In general, CH is operated in 3 phases, namely, receiving data from CM, Collection the data from CM, and forward to the sink node. Moreover, CH is assumed to be a relay node for CH to send the data to the sink node. The architecture of clustering is depicted in Fig. 1.

In WSN, clustering and routing are two significant optimization issues WSN. Most of the clustering-related routing models were examined, and numerous protocols were also deployed. Computational Intelligence (CI) methods like Neural Networks (NN), Reinforcement Learning (RL), Swarm Intelligence (SI), Evolutionary Algorithms (EA), and Fuzzy Logic (FL) have been employed to report the designing problems in WSN like CH election, routing, trust, data collection, synchronization. Since the nodes are interdependent with one another with inter-related metrics, cluster development is performed with the application of previous rules; however, it is not highly suitable. The SI-based clustering protocols sort the SN as clusters for reducing power utilization in the complete system. In the case of n SNs, there are 2N-1 solutions, and each solution is probable to be selected as CH or CM. Therefore, clustering is also meant to be a Non-deterministic Polynomial (NP)-hard problem. Followed by, EA has been applied effectively to resolve numerous NP-hard issues.

Besides, energy harvesting techniques can be incorporated to solve the energy efficiency issue. Renewable energy sources find an effective way to solve the energy efficiency problem. Also, new sensing approaches have emerged that harness power from their immediate environments, such as wind and kinetic energy. The harvested energy can be further transformed to electrical signals, which are either consumed directly or stored for later usage. Therefore, the sensor technologies need to be extended to the utilization of energy harvesting sources [5]. Though energy harvesting techniques are found to be useful, clustering and routing are still considered as the energy efficient techniques which energy harvesting is not possible under all types of applications.

For resolving the clustering and routing problem, this paper proposes a hybridization of metaheuristics based cluster-based routing (HMBCR) technique for WSN. The HMBCR technique involves brain storm optimization with levy distribution (BSO-LD) based clustering and water wave optimization with hill climbing (WWO-HC) based routing. The BSO-LD algorithm derives a fitness function (FF) for CH selection using four input parameters namely energy, distance to neighbors, distance to base station (BS), and network load. In addition, the WWO-HC technique is applied for optimal route selection to identify the inter-cluster routes to BS. A detailed set of simulations takes place to ensure the energy-efficient performance of the proposed model.

The upcoming sections of the paper are organized as follows. Section 2 elaborates on the related studies to the presented model. Section 3 presents the energy model involved in this study. The proposed HMBCR technique is discussed in section 4. The experimental results are discussed in section 5, and the study is concluded in section 6.

II. RELATED WORKS

This section explains the different clustering and routing protocols developed for WSN using metaheuristic algorithms. A new perception for hierarchical heterogeneous WSNs has presented in [6] in terms of mobile SN termed as MEACBM routing protocol. Then, Kaur and Mahajan [7] recommended Energy efficiency as the major issue in WSN. In this framework, tree-based routing protocol, Hybrid ACO, and PSO-based energy-efficient clustering methodologies have been deployed. Initially, according to the RE, cluster formation is computed, and hybrid ACO-PSO-based data aggregation is used for improvising the inter-cluster data aggregation. Mohamed *et al.* [8] investigated the optimal node degree for low-power applications. A Node Degree (ND) of Degree Constrained Tree (DCT) in identical WSN with a single BS has been applied in this study. Moreover, ND impacts the network lifetime. Finally, a Collaborative Distributed Antenna (CDA) routing protocol has been presented using transmission power to offer the node distribution. The performance results have shown the best ND, which multiplied the network duration significantly. Furthermore, the combination of DCT and CDA ensures the improvisation of network stability.

Grey Wolf Optimization (GWO) is introduced in [9] for resolving CH election issues. An appropriate FF has been utilized to approve the coverage of WSN, which is induced to GWO for identifying an optimal solution. Hence, the simulation outcome attained from the newly developed model is compared with the Low Energy adaptive clustering hierarchy (LEACH) routing protocol. There are four diverse objectives, namely, RE, lifespan, network throughput, and performance indicators. Consequently, the proposed method surpassed the LEACH in most of the protocols under the application of various indicators. An energy-effective CH election approach is developed in [10] on the basis of the Whale Optimization Algorithm (WOA) named WOA-Clustering (WOA-C) has been presented. Finally, it guides in the election of energy-aware CH according to the FF, which assumes RE of a node and the sum of energy in neighboring nodes. As a result, the applied technique was estimated by means of power efficiency, network lifespan, entire stability as well as throughput. In addition, the working principle of WOA-C has been applied over remarkable contemporary routing protocols to exhibit the supremacy of these mechanisms.

A delay and energy-sensitive routing protocol is designed in [11] to confirm the superior quality of service. The key objective of this work is to reduce the latency as well as power utilization. The WSN and actuator networks have been employed. It is comprised of sensor and actuator nodes. Here, actuators are utilized for making frequent decisions and respond accordingly to data collected by SNs. The system is sorted into clusters that are monitored by applying CH. The CH election depends upon connectivity as well as power stability. In addition, the alternate metric assures distance between counts of hops which is related to actuator nodes. It is used to enhance network scalability by limiting the communication delay and alert the actuator nodes, and mitigates the power application. At last, the obtained results imply adequate efficiency by means of communication delay as well as power application.

A routing model GECR and Genetic Algorithm (GA) relied upon energy-efficient clustering is developed in [12] to enhance the network lifespan and energy efficiency. An optimal solution accomplished from the previous system is included in a prime population for recent iteration where the search efficiency is maximized. Moreover, when the FF is developed, a load balancing mechanism is assumed, which helps in balancing the power utilization among the nodes. Finally, results have implied that the newly developed method proposed model has performed well using load balancing with minimum variance and power-efficient. Ennaciri *et al.* [13] applied a novel load balancing protocol to manage the power applied by SN in WSN. The outcomes represent that using MATLAB, performance comparison is estimated by two protocols like LEACH and Stable Election Protocol (SEP) where the quality has been ensured.

In [14], fuzzy-based unequal clustering and hybrid data transmission with ACO-based routing (FUCHAR) technique is developed to prolong the network lifetime. Here, FL is used for CH selection and ACO algorithm is used for the routing process. In [15], a multi-objective particle swarm optimization (MOPSO) algorithm is presented to optimize the cluster count in WSN to achieve energy efficiency. The MOPSO algorithm assumes the node degree and energy consumption of the nodes to elect CHs. In [16], [17], a hybridization of whale and grey wolf optimization (WGWO)-based clustering technique is presented for WSN. The utilization of two metaheuristic algorithms resulted in achieving better performance.

III. ENERGY CONSUMPTION MODEL

In general, the communication unit is composed of a transmitter and receiver. Initially, the transmitter section contains SNs which utilize maximum power to design the radio electronics and amplifier circuit. Secondly, the receiver utilizes power while receiving data based on the communicating distance. When the communication entities are isolated by a distance d and in case if it is minimum when compared with a threshold distance, then free space energy utilization mechanism has been employed to estimate the energy expended [14]; otherwise, the multipath approach has been applied. Also, a data aggregation feature is embedded for CH to BS. For transmitting a l-bit data over a distance d, the energy spent can be estimated using Eq. (1). In this model, E_{elec} is signified as energy utilized by transmitting or receiving digital circuitry for sending a single bit data. E_{tx} and E_{rx} defines the power utilized by transmitting and receiving units in order to proceed packet of length L, which depends upon the digital coding and digital modulation methodologies. E_{fs} and E_{mp} means the transmitter amplifier cost for free space mechanism (free space energy loss) and multipath model, correspondingly. The key information regarding amplifier (power amplifier) is used for controlling the setting of power where communication distance d among transmitter and receiver is lesser than d_0, then the free space power loss approach is assumed for energy evaluation.

The power required during transmission with free space mechanism is implied as,

$$E_{tx}(L,d) = LE_{elec} + LE_{fs}d^2 d \ll d_0. \tag{1}$$

When the distance d is higher than a threshold distance, then the multipath approach is employed for energy expenditure is estimated as:

$$E_{tx}\ (L, d) = LE_{elec} + LE_{mp}d^4 d \gg d_0. \tag{2}$$

Power utilization at the reception side is represented by

$$E_{rx}(L, d) = LE_{elec}, \tag{3}$$

where L implies the length of the data packet in the count of bit for communication. The estimation of d_0 takes place using

$$d_0 = \frac{\sqrt{E_{fs}}}{\sqrt{E_{mp}}}. \tag{4}$$

IV. THE PROPOSED HMBCR PROTOCOL

This section is divided into the following subheadings to provide a concise description of experimental results.

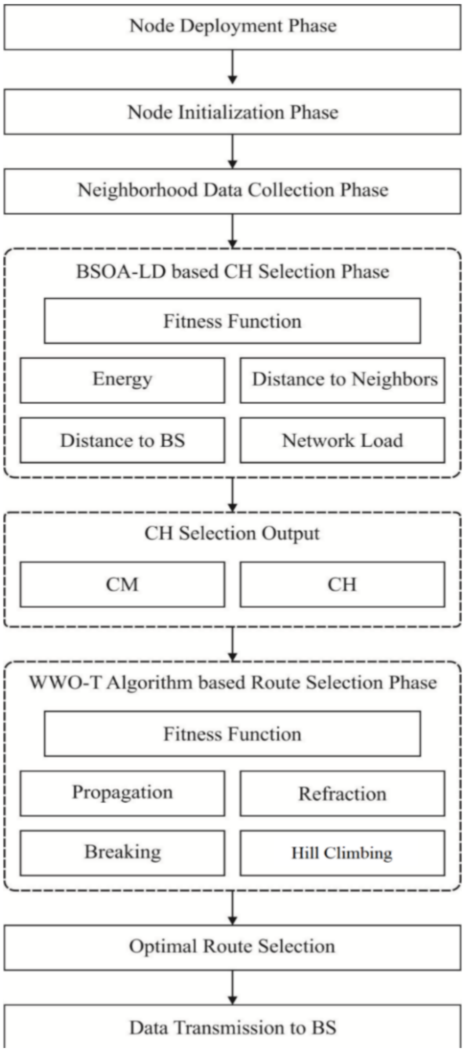

FIGURE 2. The overall process involved in the proposed model.

A. THE OVERALL SYSTEM ARCHITECTURE

The overall system architecture of the HMBCR protocol is demonstrated in Fig. 2. The detailed working process of this model is given as follows. At the initial stage, the nodes are deployed arbitrarily in the target area. Then, the initialization of the nodes takes place to gather the details related to the adjacent nodes. Afterward, the BSO-LD algorithm gets executed to determine the optimal set of CHs in the network. Finally, the data transmission takes place using the intercluster routes determined by the WWO-HC algorithm.

B. THE BSO-LD ALGORITHM-BASED CLUSTERING

Once the nodes are initialized after deployment, the BSO-LD algorithm derives the FF using four input parameters to find the optimal set of CHs. The BSO algorithm is evolved from a swarm-based meta-heuristic approach according to human brainstorming metabolism. It is a popular method in resolving the issues if it is combined and distributed diverse suggestions. According to this principle, the actual method is composed of three major phases, namely, Clustering, New individual generation, and Selection. Initially, the clustering method desires to collect identical solutions as condensed regions, therefore limiting the repetition and the same individuals. Furthermore, a novel individual has been deployed on the basis of a few rules. Initially, a novel solution has been established according to various individuals, as recommended by actual BSO that describes a probability p_{gen} which has been utilized for computing whether a new solution might be generated by massive individuals. Under the application of p_{gen}, the method improves the exploitation or exploration when a new individual is generated from a cluster and improves the local solutions; besides, producing a solution on 2 clusters are placed away from the clusters; however, it is suitable for exploration [18]. The actual technique describes 2 additional parameters, namely, $P_{one\mathrm{Cluster}}$ and $P_{two\mathrm{Cluster}}$, which refers to the possibility of developing a solution.

Consider $\mathrm{x} \in \Re^n$ as a feasible solution in an issue with n features, and $\mathcal{X} = \{\mathrm{x}_1, \mathrm{x}_2, ..,\mathrm{x}_m\}$ is a search space with m possible solutions. Once the clustering is completed, BSO provides an individual for viable solutions on the basis of rules with a copy of the optimal solution or the combination of solutions from 2 various clusters. These operations are ruled by the possibilities $p_{gen}, P_{one\mathrm{Cluster}}$, and $P_{two\mathrm{Cluster}}$. Alternatively, it also generates a new individual as a convex integration of 2 other ones. The novel solution is deployed under the application of the given formula:

$$\hat{\mathrm{x}}_i^j = \hat{\mathrm{x}}_z^j + r_1 \text{Ø}(t), \tag{5}$$

where x_i^j represents the j^{th} decision parameter of solution x_i, $r_1 \sim U(0, 1)$, t refers to the time step (iteration value). Moreover, Ø (t) is determined as given below:

$$\text{Ø}(t) = r_2 \sigma \left(\frac{0.5T - \mathrm{f}}{s}\right), \tag{6}$$

where $r_2 \sim U(0, 1)$ defines a randomly projected value from [0,1] by applying uniform distribution, σ defines the logistic sigmoid function, and T represents the overall count of iterations. Finally, the temporary individual $\hat{\mathrm{x}}$ has to be estimated. For this purpose, the minimization problem is considered, and minimum values of $f(\mathrm{x}_i)$ were also assumed. At this point, when a novel individual is maximum to the present one, then the second one is interchanged by a new solution.

For eliminating the BSOA from local optimum problem, LD is included in it. The LD is a way of mathematically initializing the sudden drift. Fig. 3 shows the flowchart of the BSOA model. The Levy flight is a random walk process in which the step length of the searching task gets enhanced with a sudden drift, as given below.

$$Levy(\alpha) \sim t^{-1-\alpha}, \quad 0 < \alpha < 2 \tag{7}$$

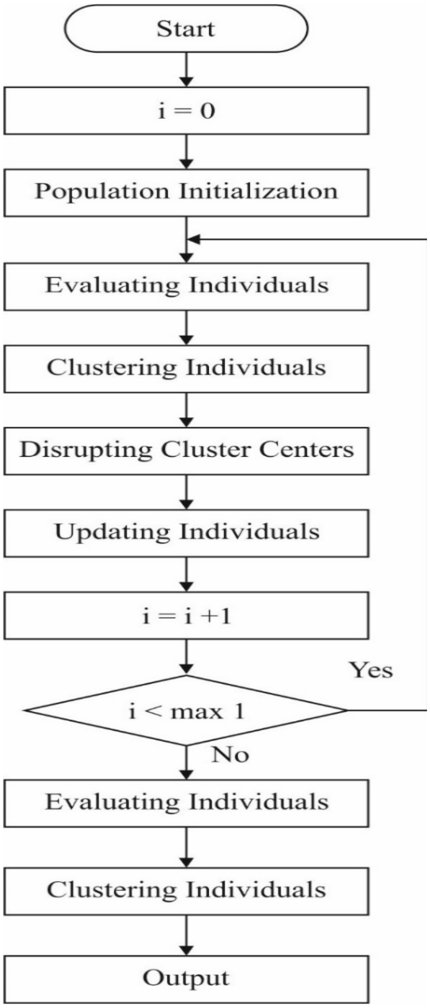

FIGURE 3. The flowchart of BSOA.

where t is an arbitrary parameter that comes under the range of (0, 1], and α denotes the stability index. In the design of LD in the searching area, it can be represented by

$$Levy\left(\beta\right) = \frac{u \times \phi}{|v|^{1/\beta}} \tag{8}$$

where u and v are the values of normal distribution, β is levy exponent and Ø is represented by

$$\phi = \left[\frac{\Gamma\left(1+\alpha\right) \times \sin\left(\frac{\pi\alpha}{2}\right)}{\Gamma\left(\frac{(1+\alpha)}{2}\right) \times \alpha \times 2^{\left(\frac{\alpha-1}{2}\right)}}\right]^{\frac{1}{\alpha}} \tag{9}$$

where α is equal to 1.5, u and v are arbitrary values. In the BSOA-LD model, next to the initializing process of population, an arbitrary individual is generated by

$$X_i = \begin{cases} X_{lb} + a \times Levy\left(\alpha\right) \times \left(X_j - X_k\right), & if\ r_1\left(\right) < r_2\left(\right) \\ X_{ub} + a \times Levy\left(\alpha\right) \times \left(X_j - X_k\right), & otherwise \end{cases} \tag{10}$$

where $r()$ is an arbitrary parameter. Once the BSOA has not been properly exploited in the search space, the Levy imposed solution contributes to the unaltered feature of the present individual.

C. APPLICATION OF BSOA-LD MODEL FOR CLUSTERING PROCESS

In general, there are four objective functions where it encloses all significant factors required for energy-effective clustering like preserving the energy by limiting the count of CH, identifying present energy ratio, reducing the distance among CH and BS, mitigation of intra-cluster distances, improved inter-cluster distance from CH, and balance the load among CHs.

The newly presented hybrid WGWO model generates an optimal solution by deriving a FF using energy, distance to neighbors, distance to BS, and network load. Therefore, FF is described in the newly deployed approach as demonstrated in the following:

$$FF = minimum\left(m_1 y_1 + m_2 y_2 + m_3 y_3 + m_4 y_4\right) \tag{11}$$

where m_1, m_2, m_3, and m_4 refer to the weight constants described by the user, and FF means the FF. Additionally, y_1, y_2, y_3, and y_4, implies the objective functions.

The presented BSOA-LD has been applied to identify an optimal solution based on the FF. Here, the solution is obtained by an agent. Thus, the optimized solution for the above-mentioned FF is composed of the least count of clusters with maximum link < quality and dynamically decided CHs with maximal residual energy (RE). The initial function is considered for conserving energy, and the energy ratio is determined as follows. If there are M nodes, R clusters, then the ratio of node's energy and present CHs energy. Eq. (12) defines the given function.

$$y_1 = \frac{\sum_{p=1}^{M} Energy\left(node_p\right)}{\sum_{q=1}^{R} Energy\left(cluster_{head\,p}\right)} \tag{12}$$

The next function determines the distance to neighbors, which is determined as a Euclidean distance among the SNs (13), as shown at the bottom of the next page.

The third function reduces the distance between CH and BS. In this model, the region is considered as $A \times A$; the overall clusters are R which is illustrated by Eq. (14), as shown at the bottom of the next page.

The final function is utilized to manage the load from CH. Eq. (15) limits the higher load among CHs. $|CN_q|$ implies the count of nodes in cluster q. Next, a region is considered as $A \times A$; total clusters are R.

$$y_4 = \frac{\mathrm{MAXIMUM}\left(\left|CN_q\right|\right)}{\frac{1}{R}\sum_{q=1}^{R}\left(\left|CN_q\right|\right)} \tag{15}$$

D. WWO-HC BASED ROUTING PROTOCOL

In general, WWO is defined as a novel method evolved from the wave motions ruled by the underneath communications of wave currents and recommended for high-dimensional global optimization issues [19]. Then, fitness is estimated conversely by a seabed depth (maximization issue) for every wave $x \in X$: the limited distance is considered as optimal fitness. In case of initialization, for a wave, the measure of wave height h is fixed as a constant h_{max} and corresponding wavelength λ is fixed to λ_0. Propagation, refraction, and breaking are three types of wave motions considered in this work.

1) PROPAGATION

This operator reflected the energy dispersion because of swirl, seabed friction, and inertial resistance [19]. Assume a wave x_i of dimension n, propagation operator generates the upgrading wave x_i as given below:

$$x'_{id} = x_i^d + r\lambda L^d, \tag{16}$$

where λ implies the wavelength in which the value is upgraded for all iterations, r means a random value from [−1, 1], and L^d denotes the length of dth dimension (1 ≤ d ≤ n). A novel position of x'_i is reallocated to a random position among a search boundary when it is placed external to the possible boundary. Once the propagation is completed, a new and previous wave is compared on the basis of fitness measures. The new waves with maximum fitness are interchanged in a population, and the wave height is reallocated as h_{max}. Alternatively, height h of x_i might be reduced by 1 and x_i is stable one that mimics energy dispersion as vortex shedding, bottom friction, and inertial resistance have been existed [20]. The updates of wavelength in all iterations are measured as shown:

$$\lambda_i\left(\mathrm{t}+1\right) = \lambda_i\left(\mathrm{t}\right)\alpha\exp\left(\frac{f\left(x_i\left(r\right)\right) - f_{min} + \varepsilon}{f_{mox} - f_{min} + \varepsilon}\right), \tag{17}$$

where t implies the recent iteration value, *fmax* and *fmin* means the superior and inferior objective values, correspondingly, α denotes the wavelength reduction coefficient and ∈ is refers to small positive value employed in eliminating zero in the denominator of the exponential term. Eq. (17) ensures that tiny wavelengths with maximum fitness waves are applicable to propagate inside limited ranges.

2) REFRACTION

The wave direction is modified when the wave ray is irregular to bottom estimation. It is evident that wave rays converge mostly in shallow regions and diverge in in-depth regions. Here, if the wave's heights have reached 0, then a refraction operator has been employed on these waves. One of the simple approaches utilized for computing position after wave refraction is given in the following:

$$\chi'_{id} = N\left(\frac{x_{besf}^d + x_i^d}{2}, \frac{|x_{besf}^d - x_i^d|}{2}\right), \tag{18}$$

where $N(\mu, \sigma)$ denotes a normal distribution with standard deviation σ and mean μ, and x_{best} is one of the optimal solutions identified. Followed by, the dth dimension of ith wave is an arbitrary value among recent dimensions as well as well-known dimensions. Once the process is completed, wave height of $xi(t+1)$ is reset to h_{max}, and the wavelength is determined as given below:

$$\lambda_i\left(\mathrm{t}+1\right) = \lambda_i\left(\mathrm{f}\right)\left(\frac{f\left(x_i\right)}{f\left(x'_i\right)}\right), \tag{19}$$

3) BREAKING

For WWO, the breaking task has been utilized on a wave $x_i, i = 1, \ldots, N$ which is capable of accomplishing a novel and optimal wave x_{best}. Also, wave breaking is used on x_{best} by deciding k dimensions in random manner $(1 < k < k_{max})$. Thus, for a dimension d, a solitary wave x'_i has been measured with the help of a given notion.

$$x'_{id} = x_i^d + N\left(0, 1\right)\beta L^d, \tag{20}$$

where β refers the breaking variable. x_{best} denotes the case of a solitary wave as it not fittest wave. Usually, the propagation operator develops maximum-fitness waves in tiny regions and minimum fitness waves in enlarged regions. A refraction operator guides the waves to eliminate search recession that results in enhancing search diversification and mitigate premature convergence. A breaking operator enables a wider exploration in challenging regions. As a result, it is noted that major wave operators exhibit the management among exploration and exploitation search. In order to increase the local searching ability, the HC effect is incorporated into the WWO algorithm [20]. HC is the easiest form of the local searching process. Primarily, it begins with a random solution and then shits iteratively from a parent-to-child solution till no optimal child solutions are identified. By the basic principle of the HC technique, it increases the local searching ability of the WWO algorithm.

$$y_2 = \sum_{q=1}^{R} \frac{\sum_{\forall \mathrm{node}_j \in \mathrm{cluster}_q} \mathrm{euclidean\_distance}\left(\mathrm{node}_j, \mathrm{cluster\_head}_q\right)}{\mathrm{minimum}_{\forall \mathrm{node}_j \in \mathrm{clusterr}_q} \mathrm{euclidean\_distance}\left(\mathrm{node}_j, \mathrm{cluster\_head}_q\right)} \tag{13}$$

$$y_3 = \frac{\frac{1}{R}\sum_{q=1}^{R} \mathrm{euclidean\_distance}\left(\mathrm{cluster\_head}_q, base-station\right)}{\frac{A}{2}} \tag{14}$$

E. APPLICATION OF WWO-HC ALGORITHM FOR ROUTE SELECTION

To find the optimal set of routes, the dimensions of all water wavers are found to be equal to CHs and the extra position is placed in the BS. Consider, $\theta^i = (\theta_1^i, \theta_2^i|\theta_{p+1}^i)$ is a i^{th} water wave, $\theta_{n_i}^i$ denotes a real value lies in the interval of [0, 1]. Next, the given function is employed to determine the subsequent hop to the BS and is defined by

$$f(x)=\{i, for\ which \left|\left(\frac{i}{k}-X_{i_f j}\right)\right| is\ minimum,\ \forall_i 1 \leq i \leq k \tag{21}$$

The intention is to determine the optimal set of routes from CHs to BS using an FF involving two parameters, namely energy and distance. Firstly, the RE of the next-hop node is determined, and the node with maximum energy is treated as a relay node. To transmit data, the source node sends to the relay node, which further forwards to BS via inter CHs. Therefore, the node with higher RE is treated as the next-hop node. The first sub-objective $f1$ is provided by:

$$f1 = \sum_{i=1}^{m} E_{CHi} \tag{22}$$

Besides, Euclidean distance is applied to determine the distance from CHs to BS. The minimization of energy dissipation is mainly based on the communication distance. In case of a lower distance, the energy will be saved significantly. Once the distance is increased, more amount of energy will be spent. So, a node with minimum distance is preferable for a relay node. So, the next ob sub-objective by means of distance is $f2$, which is referred to as:

$$f2 = \frac{1}{\sum_{i=1}^{m} dis(CH_i, NH) + dis(NH, BS)} \tag{23}$$

The above-mentioned sub-objectives are summarized into a FF as given below, where the α_1 and α_2 denotes the weights assigned to every sub-objective.

$$Fitness=\alpha_1 (f1)+\alpha_2 (f2), \quad where \sum_{i=1}^{2} \alpha_i = 1 \alpha_i \varepsilon (0, 1); \tag{24}$$

V. PERFORMANCE VALIDATION

The performance of the HMBCR protocol is implemented in the MATLAB tool. The parameters that exist in the implementation process are tabulated in Table 1 [14]. In addition, the performance evaluation of the HMBCR algorithm takes place with existing methods in terms of energy efficiency, network lifetime, packet deliver ratio (PDR), end-to-end (ETE) delay, packet loss rate (PLR). A detailed comparative results analysis with the existing FUCHAR [14], GWO [9], MO-PSO [15], and WGWO [16], [17] algorithms were made.

Table 2 and Fig. 4 show the energy efficiency analysis of the HMBCR algorithm in terms of average RE. A novel cluster-based routing technique necessitates a higher average RE to imply effective performance. The figure states that the FUCHAR algorithm has depicted inferior results by achieving higher energy dissipation with minimum average RE. Simultaneously, the GWO and MO-PSO algorithms have demonstrated slightly higher average RE over FUCHAR. At the same time, the WGWO algorithm has tried to exhibit competitive results with a moderate average RE. But the proposed HMBCR model has demonstrated superior energy efficiency over the other methods. For instance, under the execution round of 1000, the HMBCR method attains a maximum average RE of 0.9755J, whereas the FUCHAR,

TABLE 1. The parameter settings.

Parameters	Values
Target area	1000*1000m2
Location of BS	500*500m2
Node count	1000
Initial energy	1 J
Eelec	50nJ/bit
εfs	100pJ/bit/m2
εfs	100pJ/bit/m2
Bandwidth	20 kbps
Packet size	4000 bits
Node deployment	Random
Antenna direction	Omnidirectional

TABLE 2. The energy efficiency analysis of the HMBCR algorithm.

No. of Rounds	Average Residual Energy (J)				
	FUCHAR	GWO	MO-PSO	WGWO	HMBCR
0	1.0000	1.0000	1.0000	1.0000	1.0000
250	0.9805	0.9831	0.9840	0.9900	0.9955
500	0.9705	0.9781	0.9740	0.9700	0.9955
750	0.9655	0.9681	0.9540	0.9200	0.9855
1000	0.9605	0.8981	0.9240	0.8200	0.9755
1250	0.9555	0.7831	0.6890	0.7450	0.9735
1500	0.9505	0.6481	0.5240	0.7125	0.9685
1750	0.8305	0.5481	0.4540	0.6540	0.8955
2000	0.6805	0.4181	0.3140	0.5520	0.8455
2250	0.6605	0.3481	0.2290	0.4450	0.7955
2500	0.4305	0.1981	0.1840	0.3210	0.6955
2750	0.3605	0.1631	0.1140	0.2780	0.6455
3000	0.3005	0.1281	0.0540	0.1350	0.5955
3250	0.0000	0.0981	0.0290	0.0910	0.4955
3500	0.0000	0.0000	0.0210	0.0300	0.3955
3750	0.0000	0.0000	0.0000	0.0100	0.2955
4000	0.0000	0.0000	0.0000	0.0000	0.1955
4250	0.0000	0.0000	0.0000	0.0000	0.0955
4500	0.0000	0.0000	0.0000	0.0000	0.0455
4750	0.0000	0.0000	0.0000	0.0000	0.0100
5000	0.0000	0.0000	0.0000	0.0000	0.0000

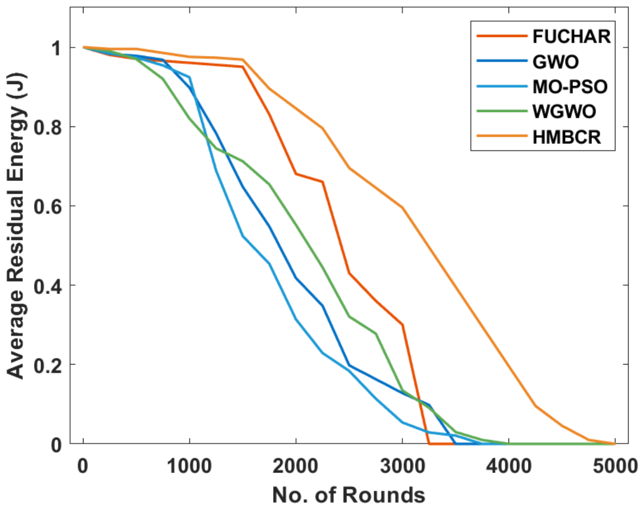

FIGURE 4. The average residual energy analysis of HMBCR model.

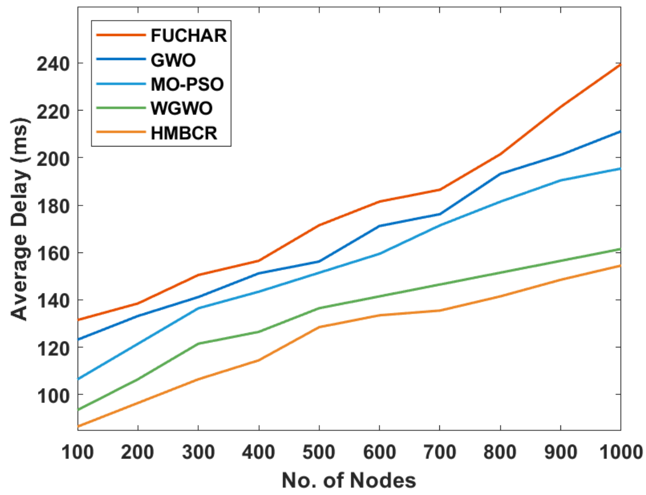

FIGURE 5. The average delay analysis of the HMBCR model.

TABLE 3. The comparative average ETE delay analysis of the HMBCR algorithm.

No. of Nodes	Average Delay (ms)				
	FUCHAR	GWO	MO-PSO	WGWO	HMBCR
100	131.50	123.20	106.46	93.50	86.50
200	138.50	133.20	121.46	106.50	96.50
300	150.50	141.20	136.46	121.50	106.50
400	156.50	151.20	143.46	126.50	114.50
500	171.50	156.20	151.46	136.50	128.50
600	181.50	171.20	159.46	141.50	133.50
700	186.50	176.20	171.46	146.50	135.50
800	201.50	193.20	181.46	151.50	141.50
900	221.50	201.20	190.46	156.50	148.50
1000	239.50	211.20	195.46	161.50	154.50

GWO, MO-PSO, and WGWO models have obtained minimum average RE of 0.9605J, 0.8981J, 0.9240J, and 0.82J. Followed by, under the execution round of 2000, the HMBCR model reaches the highest average RE of 0.8455J while the FUCHAR, GWO, MO-PSO, and WGWO methods have attained minimum average RE of 0.6805J, 0.4181J, 0.314J, and 0.552J. Concurrently, under the execution round of 3000, the HMBCR method attains a maximum average RE of 0.5955J, but the FUCHAR, GWO, MO-PSO, and WGWO approaches have attained minimum average RE of 0.3005J, 0.1281J, 0.054J, and 0.1350J. Eventually, under the execution round of 4000, the HMBCR method attains a maximum average RE of 0.1955J. The HMBCR model has accomplished maximum average RE due to the following reasons: effective selection of CHs using a fitness function involving interrelated multiple parameters and the use of multi-hop communication via optimal routes by the presented model.

Table 3 and Fig. 5 examine the average ETE delay analysis of the HMBCR algorithm with other methods. The resultant table values were notified that the FUCHAR algorithm necessitates maximum average ETE delay. Next, the GWO algorithm has exhibited a slightly lower average ETE delay. Simultaneously, the MO-PSO and WGWO algorithms have demonstrated a competitive average ETE delay over the other methods. However, a lower ETE delay has been obtained by the HMBCR technique, exhibiting its effectiveness under varying node count. For instance, in the presence of 100 nodes, the minimum average ETE delay of 86.50ms is needed by the HMBCR model, whereas a higher average ETE delay of 131.5ms, 123.2ms, 106.46ms, and 93.5ms is needed by the FUCHAR, GWO, MO-PSO, and WGWO algorithms. In line with, on the presence of 500 nodes, the minimum average ETE delay of 128.50ms is required by the HMBCR model, while a higher average ETE delay of 171.5ms, 156.2ms, 151.46ms, and 136.5ms is essential by the FUCHAR, GWO, MO-PSO, and WGWO models. On continuing with, on the presence of 1000 nodes, the minimum average ETE delay of 154.5ms is required by the HMBCR model, while a superior average ETE delay of 239.5ms, 211.2ms, 195.46ms, and 161.5ms is needed by the FUCHAR, GWO, MO-PSO, and WGWO models.

Table 4 offers the comparative average PLR analysis of the HMBCR algorithm with existing models. The simulation outcome exhibited that the FUCHAR algorithm has reached a higher PLR, indicating its inferior performance. Followed by, the GWO algorithm has shown somewhat lesser average PLR. Concurrently, the MO-PSO and WGWO procedures have established modest average PLR over the other methods. But, a minimum PLR has been attained by the HMBCR technique, showing its effectiveness under variable node count. For instance, under 100 nodes count, a lower PLR of 0.0510is needed by the HMBCR model, whereas a maximum PLR of 0.2310, 0.1410, 0.0870, and 0.0710 is needed by the FUCHAR, GWO, MO-PSO, and WGWO algorithms. In the same way, under 500 nodes count, a lower PLR of 0.0865 is needed by the HMBCR model, while a

TABLE 4. The comparative packet loss rate analysis of the HMBCR algorithm.

No. of Nodes	Packet Loss Rate				
	FUCHAR	GWO	MO-PSO	WGWO	HMBCR
100	0.2310	0.1410	0.0870	0.0710	0.0510
200	0.2410	0.1610	0.1010	0.0810	0.0565
300	0.2460	0.1910	0.1110	0.0910	0.0649
400	0.2590	0.2110	0.1410	0.1410	0.0775
500	0.2930	0.2310	0.1610	0.1510	0.0865
600	0.3100	0.2610	0.2010	0.1710	0.0965
700	0.3470	0.2810	0.2110	0.1910	0.1075
800	0.3960	0.2910	0.2410	0.2110	0.1265
900	0.4300	0.3010	0.2610	0.2310	0.1456
1000	0.5200	0.3060	0.2910	0.2510	0.1710

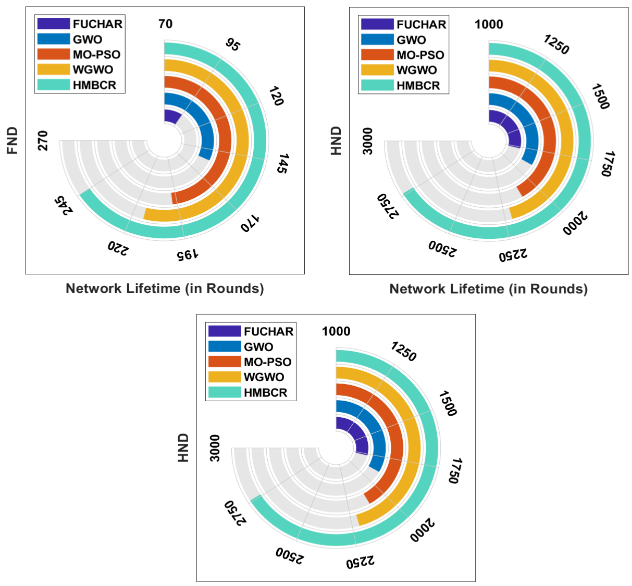

FIGURE 6. The network lifetime analysis of the HMBCR model.

maximum PLR of 0.2930, 0.2310, 0.1610, and 0.1510 is essential by the FUCHAR, GWO, MO-PSO, and WGWO models. Afterward, under 1000 node counts, a minimum PLR of 0.1710 is needed by the HMBCR model, but a maximum PLR of 0.5200, 0.3060, 0.2910, and 0.2510 is needed by the FUCHAR, GWO, MO-PSO, and WGWO models.

Table 5 and Fig. 6 demonstrate the network lifetime analysis of the HMBCR algorithm with respect to first node die (FND), half node die (HND), and last node die (LND). The table values signified that the HMBCR model has extended the network lifetime considerably by attaining FND of 245 rounds, whereas the FUCHAR, GWO, MO-PSO, and WGWO algorithms have reached to an earlier FND of 95, 155, 198, and 214 rounds, respectively. Similarly, in terms of HND, the lengthened HND are obtained by the HMBCR model with 2759 rounds. At the same time, the FUCHAR,

TABLE 5. The network lifetime analysis of the HMBCR algorithm.

Measures	Network Lifetime (in Rounds)				
	FUCHAR	GWO	MO-PSO	WGWO	HMBCR
FND	95	155	198	214	245
HND	1770	1890	2111	2214	2759
LND	3021	3410	3544	3934	4865

TABLE 6. The number of alive nodes analysis of the HMBCR algorithm.

No. of Rounds	Number of Alive Nodes				
	FUCHAR	GWO	MO-PSO	WGWO	HMBCR
0	1000	1000	1000	1000	1000
250	941	955	978	981	995
500	875	884	891	901	914
750	801	865	871	881	894
1000	754	818	824	834	851
1250	645	783	727	744	765
1500	601	648	614	712	714
1750	512	587	600	654	695
2000	458	417	518	528	614
2250	315	301	330	445	598
2500	298	198	281	321	555
2750	185	160	166	273	501
3000	99	121	154	218	488
3250	0	84	99	154	465
3500	0	0	11	97	395
3750	0	0	0	35	342
4000	0	0	0	0	295
4250	0	0	0	0	145
4500	0	0	0	0	54
4750	0	0	0	0	7
5000	0	0	0	0	0

GWO, MO-PSO, and WGWO algorithms have led to the HND at the earlier rounds of 1770, 1890, 2111, and 2214 rounds, respectively. Finally, the maximum network lifetime is exhibited by the HMBCR model has reached a higher LND of 4865 rounds, which is considerably higher than the compared methods.

Another way of determining the network lifetime is the analysis of the number of alive nodes and is shown in Table 6 and Fig. 7. The table values displayed that the HMBCR model has reached a maximum network lifetime by achieving a higher number of alive nodes, whereas the FUCHAR, GWO, MO-PSO, and WGWO algorithms have shown a lower number of alive nodes. For instance, under the existence of 1000 rounds, the maximum alive node count of 851 nodes, whereas the FUCHAR, GWO, MO-PSO, and WGWO models have achieved a lower alive node count of 754, 818, 824, and 834 rounds, respectively. Moreover, under the existence of 2000 rounds, the highest alive node count of 614 nodes while the FUCHAR, GWO, MO-PSO, and WGWO models have attained a lower alive node count of 458, 417, 518, and 528 rounds correspondingly. Furthermore, under the existence of 3000 rounds, the superior alive node count of 488 nodes while the FUCHAR, GWO, MO-PSO, and WGWO models have attained a lower alive

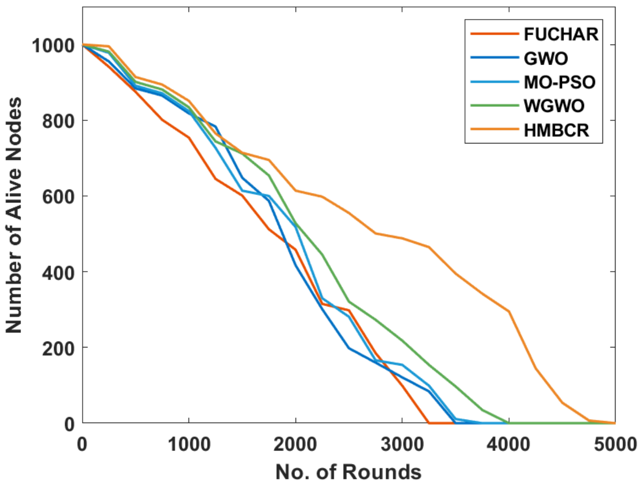

FIGURE 7. The alive nodes analysis of HMBCR model.

TABLE 7. The comparative PDR analysis of the HMBCR algorithm.

No. of Nodes	PDR				
	FUCHAR	GWO	MO-PSO	WGWO	HMBCR
100	0.8450	0.8685	0.8854	0.9014	0.9857
200	0.8250	0.8545	0.8754	0.8724	0.9802
300	0.7950	0.8445	0.8654	0.8654	0.9718
400	0.7750	0.8145	0.8154	0.8528	0.9592
500	0.7550	0.7945	0.8054	0.8455	0.9502
600	0.7250	0.7545	0.7854	0.8328	0.9402
700	0.7050	0.7445	0.7654	0.8255	0.9292
800	0.6950	0.7145	0.7454	0.8161	0.9102
900	0.6850	0.6945	0.7254	0.8214	0.8911
1000	0.6800	0.6645	0.7054	0.7854	0.8657

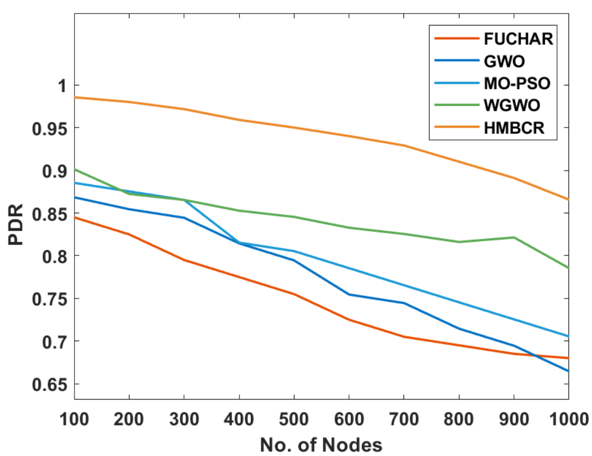

FIGURE 8. The PDR analysis of the HMBCR model.

node count of 99, 121, 154, and 218 rounds correspondingly. At last, under the existence of 4000 rounds, the maximum alive node count of 295 nodes.

A PDR analysis of the HMBCR algorithm with existing methods takes place, as shown in Table 7 and Fig. 8. As shown in the figure, the HMBCR model has shown an effective outcome by obtaining maximum PDR under all the varying node count. Though the MO-PSO and WGWO algorithms have surpassed the FUCHAR and GWO algorithms, it has failed to outperform the proposed HMBCR model. For instance, in the existence of 100 nodes, the HMBCR model has obtained a maximum PDR of 0.9857, whereas the FUCHAR, GWO, MO-PSO, and WGWO algorithms have demonstrated a slightly lower PDR of 0.8450, 0.8685, 0.8854, and 0.9014, respectively.

Along with that, in the existence of 500 nodes, the HMBCR model has reached the highest PDR of 0.9502, whereas the FUCHAR, GWO, MO-PSO, and WGWO models have exhibited a somewhat lower PDR of 0.7550, 0.7945, 0.8054, and 0.8455, respectively. Along with that, in the existence of 1000 nodes, the HMBCR model has obtained the highest PDR of 0.8657 while the FUCHAR, GWO, MO-PSO, and WGWO algorithms have outperformed a somewhat lower PDR of 0.6800, 0.6645, 0.7054, and 0.7854 correspondingly. The above-mentioned tables and figures ensure that the HMBCR model has achieved proficient performance over the compared methods by achieving maximum network lifetime and energy efficiency.

VI. CONCLUSION

This study has designed an effective HMBCR protocol to improve energy efficiency and network lifetime in WSN. The HMBCR technique operates on two levels, namely BSO-LD-based clustering and WWO-HC-based routing. At the initial stage, the nodes are deployed arbitrarily in the target area. Then, the initialization of the nodes takes place to gather the details related to the adjacent nodes. Afterward, the BSO-LD algorithm gets executed to determine the optimal set of CHs in the network. Finally, the data transmission takes place using the inter-cluster routes determined by the WWO-HC algorithm. In order to validate the performance of the HMBCR technique, an extensive set of simulations was carried out. The experimental results verified that the HMBCR technique outperformed the previous methods in terms of energy efficiency, network lifetime, PDR, ETE delay, and PLR. As a part of the future scope, the data aggregation techniques can be integrated into the HMBCR to further minimize energy dissipation. In addition, to address the power supply issue with the goal to obtain perpetual and unattended WSNs, in the future, energy harvesting technologies can be used to power the sensor nodes and thus achieve the goal of perpetual network operation. Besides, the hot spot issue in WSN can be addressed by the use of metaheuristic-based unequal clustering techniques.

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REFERENCES

[1] K. Sohraby, D. Minoli, and T. Znati, *Wireless Sensor Networks: Technology, Protocols, and Applications*. Hoboken, NJ, USA: Wiley, 2007.

[2] G. Anastasi, M. Conti, M. Di Francesco, and A. Passarella, "Energy conservation in wireless sensor networks: A survey," *Ad Hoc Netw.*, vol. 7, no. 3, pp. 537–568, May 2009, doi: 10.1016/jadhoc200806003.

[3] I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "Wireless sensor networks: A survey," *Comput. Netw.*, vol. 38, no. 4, pp. 393–422, 2002, doi: 10.1016/S1389-1286(01)00302-4.

[4] X. Liu, "A survey on clustering routing protocols in wireless sensor networks," *Sensors*, vol. 12, no. 8, pp. 11113–11153, Aug. 2012.

[5] M. H. Alsharif, S. Kim, and N. Kuruoğlu, "Energy harvesting techniques for wireless sensor networks/radio-frequency identification: A review," *Symmetry*, vol. 11, no. 7, p. 865, Jul. 2019.

[6] A. S. Toor and A. K. Jain, "Energy aware cluster based multi-hop energy efficient routing protocol using multiple mobile nodes (MEACBM) in wireless sensor networks," *AEU Int. J. Electron. Commun.*, vol. 102, pp. 41–53, Apr. 2019.

[7] S. Kaur and R. Mahajan, "Hybrid meta-heuristic optimization based energy efficient protocol for wireless sensor networks," *Egyptian Informat. J.*, vol. 19, no. 3, pp. 145–150, Nov. 2018.

[8] R. E. Mohamed, W. R. Ghanem, A. T. Khalil, M. Elhoseny, M. Sajjad, and M. A. Mohamed, "Energy efficient collaborative proactive routing protocol for wireless sensor network," *Comput. Netw.*, vol. 142, pp. 154–167, Sep. 2018.

[9] M. Sharawi and E. Emary, "Impact of grey wolf optimization on WSN cluster formation and lifetime expansion," in *Proc. 9th Int. Conf. Adv. Comput. Intell. (ICACI)*, Feb. 2017, pp. 157–162.

[10] A. R. Jadhav and T. Shankar, "Whale optimization based energy-efficient cluster head selection algorithm for wireless sensor networks," Nov. 2017, *arXiv:1711.09389*. [Online]. Available: https://arxiv.org/abs/1711.09389

[11] S. Yahiaoui, M. Omar, A. Bouabdallah, E. Natalizio, and Y. Challal, "An energy efficient and QoS aware routing protocol for wireless sensor and actuator networks," *AEU-Int. J. Electron. Commun.*, vol. 83, pp. 193–203, Jan. 2018.

[12] T. Wang, G. Zhang, X. Yang, and A. Vajdi, "Genetic algorithm for energy-efficient clustering and routing in wireless sensor networks," *J. Syst. Softw.*, vol. 146, pp. 196–214, Dec. 2018.

[13] A. Ennaciri, M. Erritali, and J. Bengourram, "Load balancing protocol (EESAA) to improve quality of service in wireless sensor network," *Procedia Comput. Sci.*, vol. 151, pp. 1140–1145, Jan. 2019.

[14] S. Arjunan and P. Sujatha, "Lifetime maximization of wireless sensor network using fuzzy based unequal clustering and ACO based routing hybrid protocol," *Int. J. Speech Technol.*, vol. 48, no. 8, pp. 2229–2246, Aug. 2018.

[15] H. Ali, W. Shahzad, and F. A. Khan, "Energy-efficient clustering in mobile ad-hoc networks using multi-objective particle swarm optimization," *Appl. Soft Comput.*, vol. 12, no. 7, pp. 1913–1928, Jul. 2012.

[16] R. S. Rathore, S. Sangwan, S. Prakash, K. Adhikari, R. Kharel, and Y. Cao, "Hybrid WGWO: Whale grey wolf optimization-based novel energy-efficient clustering for EH-WSNs," *EURASIP J. Wireless Commun. Netw.*, vol. 2020, pp. 1–28, May 2020.

[17] J. P. Papa, G. H. Rosa, A. N. de Souza, and L. C. Afonso, "Feature selection through binary brain storm optimization," *Comput. Elect. Eng.*, vol. 72, pp. 468–481, 2018.

[18] Y.-J. Zheng, "Water wave optimization: A new nature-inspired metaheuristic," *Comput. Oper. Res.*, vol. 55, pp. 1–11, Mar. 2015.

[19] A. M. Ibrahim, M. A. Tawhid, and R. K. Ward, "A binary water wave optimization for feature selection," *Int. J. Approx. Reasoning*, vol. 120, pp. 74–91, 2020.

[20] B. H. Abed-Alguni and F. Alkhateeb, "Intelligent hybrid cuckoo search and β-hill climbing algorithm," *J. King Saud Univ.-Comput. Inf. Sci.*, vol. 32, no. 2, pp. 159–173, 2020.