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ARTICLE

HYBRIDIZATION OF MODIFIED GREY WOLF OPTIMIZATION WITH INERTIA PARTICLE SWARM OPTIMIZATION BASED CLUSTERING TECHNIQUE IN WIRELESS SENSOR NETWORKS

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ABSTRACT

Wireless Sensor Networks (WSN) become a hot research topic and is commonly employed for data gathering applications. Energy efficiency is treated as an important issue in the design of WSN. As the clustering technique helps to achieve energy efficiency in WSN, several works have been carried out on the proper selection of cluster heads (CHs). Clustering is assumed as an NP hard problem and metaheuristic algorithms are applied for resolving it. This paper presents a hybridization of modified grey wolf optimization algorithm and inertia particle swarm optimization with dynamic velocities (IPSO-DV) called HMGWOIPSO-DV based clustering technique in WSN. The proposed algorithm selects CHs in two levels namely IPSO-DV based tentative CH selection and MGWO based final CH selection. Besides, the presented model derived a fitness function by the use of residual energy, distance to base station (BS), and distance to nearby nodes. The proposed model has the capability of competently choosing the CHs, attains energy efficiency and maximum network lifetime. The performance of the presented model takes place under diverse aspects and the obtained experimental results ensured the goodness of the presented model.

KEY WORDS
Clustering, Energy efficiency, Metaheuristics, GWO algorithm, PSO algorithm

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INTRODUCTION

Wireless sensor networks (WSNs) are composed of a massive collection of nodes to observe and save the physical parameters in the environment [1]. In WSN, the node distribution is arbitrary. It is placed in the unmanned regions where the batteries cannot be replaced and it cannot be recharged easily, and the nodes are distributed in a random fashion. The count of nodes is maximum and initial power has been employed for charging the battery. Hence, the power applications as well as network lifespan are the major constraints which affect the network [2]. The data gathered by nodes are forwarded to base station (BS) or sink for computation. Data transmission is processed in a single-hop or multi-hop fashion [3]. The main applications of WSNs are observing forest fires, managing the condition of serious patients, armed forces as well as traffic [4]. Generally, the major challenges of WSN are fault tolerance, scalability, costs, hardware constraints, consistency, WSN topology, transmission environment and power utilization. The 2 methods applied for enhancing the WSNs lifespan are Clustering and Routing. In clustering phase, a collection of sensor nodes are fixed in a class named a cluster on the basis of general parameters.

An effectively qualified node in a cluster is termed as Cluster Head (CH). The responsibility of CH is to gather the data collected from Cluster Members (CM) and send it to BS which depends upon the data transmission. The CHs send the received data to sink using single-hop transmission, while CHs forwards the obtained data to higher-level CHs while multi-hop transmission and higher-level CHs sends the data to sink. Multi-hop transmission is often applied in large-scale networks. Basically, CM is classified into 2 classes which are composed of general nodes and CHs. Thus, few meta-heuristic approaches and Computational intelligence (CI) methodologies like artificial bee colony (ABC), artificial immune systems (AIS), Reinforcement learning (RL), Evolutionary Algorithms (EA) has been employed for the process to resolve the NP-hard optimization problem. Transmitting data to BS from the sensor node is performed by best CH which is a major challenge for routing protocol. Best CH election model results in energy reduction, latency, distance, and so forth.

The combined particle swarm optimization (PSO) and Fuzzy-related CH election approach have been presented to serve an efficient clusters-aided routing process to expand the network lifetime [5]. The CH election model applies the advantages of PSO to accomplish clustering according to the data correlated with the scientific position. Followed by, it is composed of an enhanced PSO method to compute effective CH nodes from a hierarchical topology network. It is processed to enhance the networked lifestyle with a limited degree of sensor nodes' fatality. Besides, a combined Simulated Annealing (SA) and Differential Evolution (DE) related CH election method has been projected for choosing best count of CH nodes in the clustering process [6]. The unified method highly focuses on eliminating the premature death of CH nodes to accomplish a prolonged network lifecycle. LEACH, Harmony Search Algorithm (HSA), modified HSA, and DE methods are employed for analyzing purposes.

The Enhanced Artificial Fish Swarm Algorithm (EAFSA) has been projected to reduce the power application of a system by effective CH election process [7]. The EAFSA has the advantages of foraging characteristic of the fish swarm to extract a feasible count of features that contributes to frequent CH selection. It has the fitness to estimate and validate the ability of sensor nodes to CH conversion. Moreover, it is estimated over GA and variant LEACH aided CH election schemes. An ABC-related CH election process is applied to enhance the effectiveness of the developed cluster according to the evaluation of multi-objective fitness function [8]. The ABC-based model employed the condition of least hop-count to maintain capable data transmission. It is considered for reducing initial power consumption with improved throughput, packet delivery ratio (PDR) as well as network lifetime. A combined PSO and ACO-based clustering model has been presented to improve the data and energy dispersion effectively [9]. It applied the primitive parameter of Residual Energy (RE) and intra-cluster distance for developing FF which intends to accomplish data aggregation process. It utilized multi-dimensional features of sensors for determining the importance to find the responsibility of CH in a system. Furthermore, it ensured a phenomenal enhancement in network duration than swarm-intelligent (SI) models for examination.

This paper presents a hybridization of modified grey wolf optimization algorithm and inertia particle swarm optimization with dynamic velocities (IPSO-DV) called HMGWOIPSO-DV based clustering technique in WSN. The proposed algorithm selects CHs in two levels namely IPSO-DV based tentative CH selection and MGWO based final CH selection. Besides, the presented model derived a fitness function by the use of residual energy, distance to base station (BS), and distance to nearby nodes. The proposed model has the capability of competently choosing the CHs, attains energy efficiency and maximum network lifetime. The performance of the presented model takes place under diverse aspects and the obtained experimental results ensured the goodness of the presented model.

MATERIALS AND METHODS

The major theme of this model is to decide essential CHs among the ordinary sensors by assuming the power efficiency; thus the network lifecycle can be extended. In order to select the CH with power efficiency, remaining energy of the sensor nodes and many other distance parameters are considered with average intra-cluster distance among the sensors and the distance from BS. The CH process is carried out place under 2 stages like Tentative CH selection by applying IPSO-DV model as well as final CH election by using MGWO-LF model. [Fig. 1] shows the working process of proposed method.

Derivation of fitness function

Assume f_1 as a function of average intra-cluster and BS distance of CHs. It is mandatory to reduce f_1 for selecting best CH. Secondly, f_2 is a function that is an inverse of overall energy for elected CH. For normalizing objective functions the measures have to be from (0, 1). Such functions would be applied to retrieve Fitness Function (FF) for optimization approach as depicted in the function:

$$\min F = \alpha \times f_1 + (1-\alpha) \times f_2 \qquad (1)$$

Subject to

$$dis(s_i, CH_j) \le d_{max}, \quad \forall s_i \in S, \quad CH_j \in C \qquad (2)$$

$$dis(CH_j, BS) \le R_{max}, \quad \forall CH_j \in S \qquad (3)$$

$$E_{CH_j} > T_H, \quad 1 \le j \le m \qquad (4)$$

$$0 < \alpha < 1 \qquad (5)$$

$$0 < f_1, f_1 < 1 \qquad (6)$$

Average intra-cluster distance

It determines the average sum of distances of sensor nodes from the elected CH, where $\frac{1}{l_i}\sum_{i=1}^{l_i} dis\ (s_i, CH_j)$. For intra-cluster communication, the sensor nodes intake few energy while transferring data to CH. For consuming minimal energy, the average intra-cluster communication distance has to be reduced. It refers that the selected CH is closer to sensor nodes.

Average sink distance

It is defined as a ratio of distance among CH_j and BS to count of sensor nodes l_i in CH_j i.e. $\frac{1}{l_i} dis(CH_j, BS)$. In case of data routing phase, every CH has to route the collected data to sink. Hence, in order to minimize the power consumption, the distance of CHs from BS should be limited. Then, the objective f_1 for best selection is reducing average intra-cluster as well as BS distance of the CHs.

$$\min f_1 = \sum_{j=1}^{m} \frac{1}{l_j}\left(\sum_{i=1}^{l_j} dis(s_i, CH_j) + dis(CH_j, BS)\right) \qquad (7)$$

Energy Parameter

E_{CH_j} refers to the power of CH_j, $1 \leq j \leq m$ that is elected from normal sensor nodes iteratively. $\sum_{j=1}^{m} E_{CH_j}$ would be the overall energy for elected CHs. Thus, while the optimal CH election is processed, it is better to limit the overall energy of decided CHs, where the reciprocal has to be reduced.

$$\min f_2 = \frac{1}{\sum_{j=1}^{m}\left(E_{CH_j}\right)} \quad (8)$$

In the presented model, it is limited to 2 objective functions and does not affect one another. Hence, the 2 functions are combined to offer best outcomes.

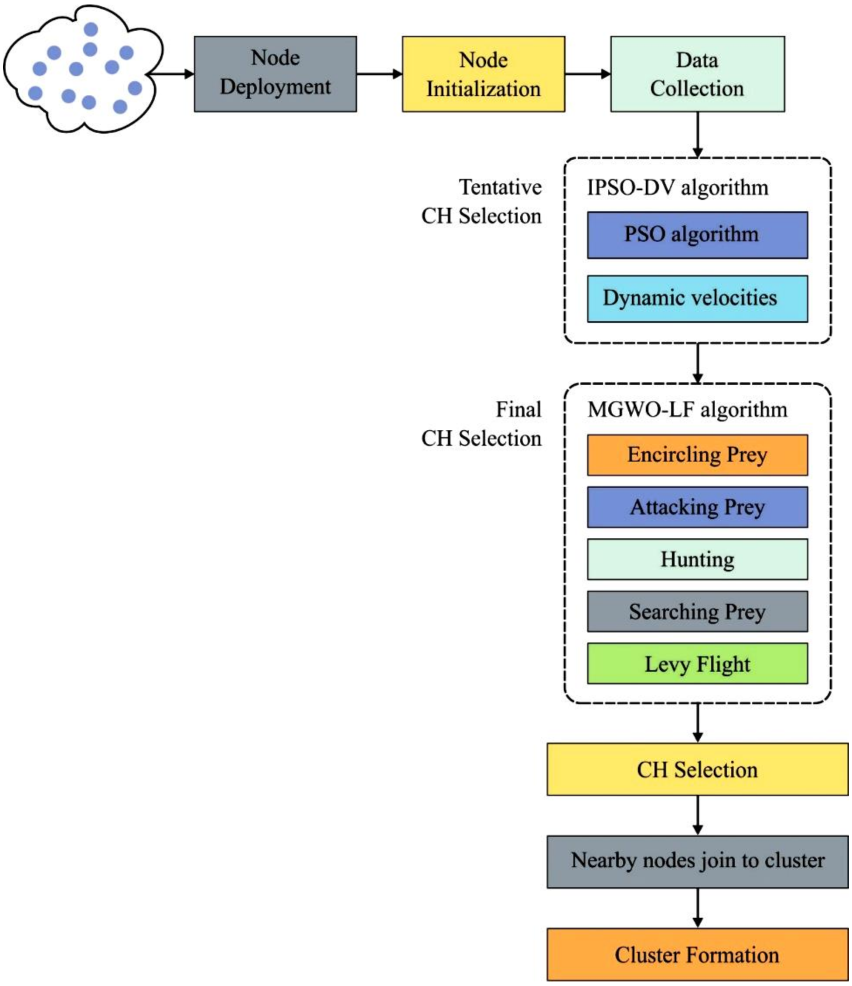

Fig. 1: Overall working process of HMGWOIPSO-DV model

IPSO-DV algorithm based Tentative CH Selection

In order to enhance the function of traditional PSO model, dynamic velocities has been used. The novel velocity of IPSO-DV is extended as given below:

$$v_{ij}(t+1) = \begin{cases} wv_{ij}(t) + c_1 r_1\left(pbest_{ij} - x_{ij}(t)\right) + c_2 r_2\left(gbest_j - x_{ij}(t)\right) & if r1 > 0.5 \\ \tau\left(v_{ij}(t) + c\left(P_{mj} - x_{ij}(t)\right)\right) & otherwise \end{cases} \quad (9)$$

where v_{ij} refers the velocity of particle i in a dimension j at t^{th} generations, r1 and r2 shows the uniform random values from [0,1], c1 and c2 showcases the cognitive as well as social coefficient parameters.

$$w = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} \times t \quad (10)$$

where w_{max} w_{min} defines the high and low values of inertia weight.

$$\tau = \frac{2}{\left|2 - c - \sqrt{c^2 - 4c}\right|} and c = c_1 + c_2, c > 4 \qquad (11)$$

and

$$P_{mj} = \frac{c_1 pbest_{ij} + c_2 gbest_j}{c} \qquad (12)$$

The place of a particle upgraded with the help of given function:

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \qquad (13)$$

A cluster is created by sink on the basis of centralized clustering. For clustering BS, data is broadcasted as messages for all sensor nodes. Behind receiving the message, it sends the node data such as node ID, position, energy-loss and energy loss ratio as well as current energy to send BS. The BS deploys clusters under the application of IPSO-DV method and telecasts a cluster- message for sensors where it has a cluster. All sensors store the message and invoke CH selection process. Then, sensor nodes retain "my cluster list." The iteration is invoked for selecting CH. In all rounds, lbest solution is assumed as particle with maximum value than so called as global best (gbest) solution. Finally, particle with gbest solution is approved as best CH.

MGWO-LF based Final CH Selection

The traditional GWO model concentrates on hunters towards the prey on the basis of α, β, and δ (leader dominant wolves). Thus, population of GWO is limited towards stagnation in LO for many cases. Therefore, GWO's problem of inferior convergence is assumed to be the major issues. Then, effective GWO model is not suitable for computing better modification from exploration to exploitation phases. From the previous application, LF has been employed. The LF guides GWO searching operation on the basis of exploring patterns. Using this model, it makes sure that GWO is appropriate for handling global exploration efficiently. Besides, the stagnation problems are resolved. Additionally, the qualities of candidate solutions are improved in Lévy- based GWO for complete process. At the initial phase, portion of delta wolves in social behavior is operated by other wolves and incorporated LF method.

In LGWO, delta wolves are not employed since the hunting operation is performed under various conditions. Actually, updating and initialization of wolves affects the entire whole searching operation. It is highlighted that the dominant nature of wolves guides GWO for saving best solutions which guides remaining candidates of population. Followed by, social behavior becomes effective at the time of using 3 kinds of wolves like alpha, beta and omega. Thus, the place of wolves in LGWO is enhanced on the basis of β types using provided equation:

$$\vec{X}(t) = 0.5 \times (\vec{X} - \vec{A}\vec{D} + \vec{X} - \vec{A}\vec{D}) \,. \qquad (14)$$

In this approach, the actions are performed towards best minima across search space. Followed by, random walks may be suitable in developing the animal actions. Lévy motion is named as diverse non-Gaussian random principles in which random steps are processed on the basis of Lévy stable distribution. Lévy distribution is projected by clear power- law function as given below:

$$L(s) - |s|^{-1-\beta}, 0 < \beta \le 2, \qquad (15)$$

where s implies the parameter and β refers the Lévy index to balance the scalability. The Lévy distribution is formulated as:

$$L(s,\gamma,\mu) = \begin{cases} \sqrt{\frac{\gamma}{2\pi}} \exp\left[-\frac{\gamma}{2(s-\mu)}\right] \frac{1}{(s-\mu)^{\frac{3}{2}}} & 0 < \mu < s < \infty \\ 0 & s \le 0 \end{cases}, \qquad (16)$$

where μ refers a shifting parameter and $\gamma > 0$ denotes a reliable parameter. Lévy distribution is reformed according to Fourier transform (FT) as given in the following:

$$F(k) = \exp\left[-\alpha |k|^{\beta}\right], 0 < \beta \le 2, \qquad (17)$$

Where α expressed the variable from [−1, 1], so called as skewness and scale factor. According to the literature, diverse values of β influence the architecture of LF distribution. While measures of β are limited, prolonged jumps are created; or else, LF can generate lesser jumps utilizing maximum values of β. Based on the Exploration factor, the searching is randomly distributed objects, while computing Lévy walk on LF-based path along with static velocity. Nevertheless, it is advantageous to imply hunting model of wolves in GWO based on the LF model. In LF assists LGWO in resembling wolves' hunting nature in practical time

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than GWO. Moreover, it is used for LF as a secondary objective that resolves the stagnation problems of GWO. Thus, latter modification to GWO, novel places are defined as:

$$\vec{X}_{new}(t)=\begin{cases}0.5\times\left(\vec{X}_\alpha-\vec{A}_1\vec{D}_\alpha+\vec{X}_\beta-\vec{A}_2\vec{D}_\beta\right)+\alpha\oplus Levi(\beta) & |A|>0.5\\ 0.5\times\left(\vec{X}_\alpha-\vec{A}_1\vec{D}_\alpha+\vec{X}_\beta-\vec{A}_2\vec{D}_\beta\right) & |A|<0.5\end{cases}, \quad (18)$$

where it depicts the step size to relevant for scales of problems, β implies the Lévy index from $(0,2)$ and $\oplus$ projects the entry wise improvisation. According to the value of $|A|$, the novel operator reforms wolves to gain best management among exploration as well as exploitation due to the LF- based jumps. During this point, adjusted GWO is suitable for accomplishing best outcomes, there is a possible LGWO for utilizing and improves optimal-qualified decisions. Moreover, these operators improve the exploitive nature of wolves in last rounds. Followed by, x implies aarbitrary quantity to dimension of wolves. Thus, if$|A|>0.5$, the operator is maximized as:

$$\vec{X}_{new}(t)=0.5\times\left(\vec{X}_\alpha-\vec{A}_1\vec{D}_\alpha+\vec{X}_\beta-\vec{A}_2\vec{D}_\beta\right)+rand\ (size\ (D))\oplus Levi(\beta), \quad (19)$$

where$D$ implies the dimension. Mantegna method is accurate model for providing stochastic variables in which the probability density is changed to Lévy steady distribution specifically balanced by a parameter $(\alpha(0.3<\alpha<1.99)$. So, Mantegna principle is used for accomplishing LF for complete exploration operation. Then, in Eq. (19), step size is computed by:

$$rand\ (size(Dim))\oplus Levi(\beta)\sim 0.01\frac{u}{v^{-\beta}}(\vec{X}(t)-\overrightarrow{X^{\alpha}}(t))\,, \quad (20)$$

where$u$ and v values can be attained on the basis of normal distributions;

$$u\sim N(0,\sigma_u^2),\ v\sim N(0,\sigma_v^2)\,, \quad (21)$$

with

$$\sigma_u=\left[\frac{\Gamma(1+\beta)\sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right)\beta\times 2^{\frac{\beta-1}{2}}}\right]^{\frac{1}{\beta}},\ \sigma_v=1, \quad (22)$$

where Γ refers the classical gamma function. During this model, β variable is dynamic, hence an arbitrary value from $(0,2)$ interval must be chosen in iterations for LF operation. Followed by, LF offers lower and occasional long-distance jumps. The random β attribute would improvise exploitation and exploration movements between the iterations.

RESULTS AND DISCUSSION

This section validates the efficient performance of the proposed technique with respect to count of alive nodes, dead nodes, and network stability. For comparative purposes, different methods are utilized [10]. [Table 1] depicts the parameter settings.

Table 1: Parameter Settings

Parameter	Value
Network dimension	$100*100m^2$
Node count	100,300,500
Number of BS	1
Initial energy	0.5
Transmit/Receive Energy E_{elec}	50nJ/bit
Threshold distance (d_0)	80m
Packet size	2000 bits
Population size (P)	100

Fig. 2 depicts the detailed alive node analysis of the presented and existing models under a varying number of nodes. From the figure, it is apparent that the HPSOGWO and FBECS algorithms have exhibited poor network lifetime by attaining minimum number of alive nodes. Followed by, the IPSO-DV algorithm has tried to show better network lifetime over the previous models with slightly higher number of alive nodes. Simultaneously, the MGWO-LF algorithm has demonstrated somewhat better network lifetime over the compared methods. But the proposed method has showcased excellent results by attaining maximum network lifetime with the maximum number of alive nodes. For instance, under the varying node count of 100 with the execution round of 1000, the presented model has reached to a maximum number of 50 nodes whereas the MGWO-LF, IPSO-DV, HPSOGWO and FBECS algorithms have attained a minimum number of 28, 25, 6 and 6 nodes respectively. Besides, under the varying node count of 300 with the execution round of 1000, the presented model has reached to a higher number of 153 nodes whereas the

MGWO-LF, IPSO-DV, HPSOGWO, and FBECS algorithms have attained a minimum number of 120, 40, 6, and 0 nodes respectively. Also, under the varying node count of 500 with the execution round of 1000, the presented model has offered a superior performance with a higher number of 210 nodes whereas the MGWO-LF, IPSO-DV, HPSOGWO, and FBECS algorithms have attained a minimum number of 160, 140, 26 and 5 nodes respectively.

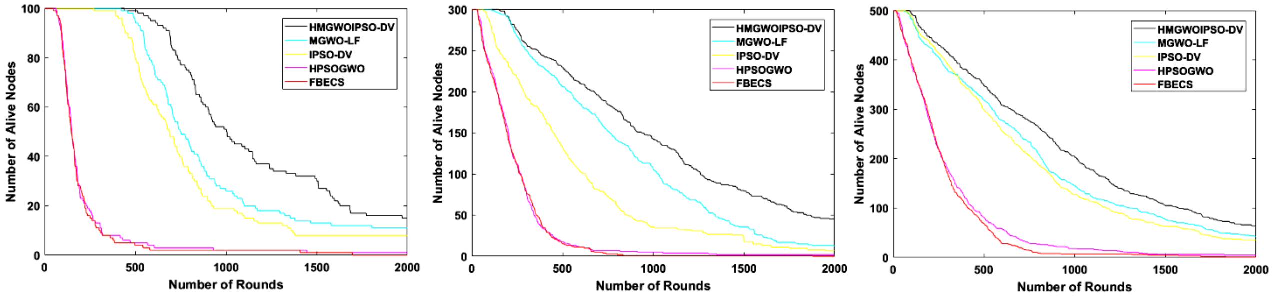

Fig. 2: Alive node analysis of proposed model under varying node count

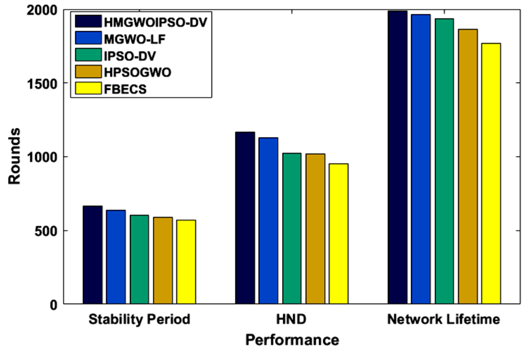

Fig. 3: Network lifetime analysis

Fig. 3 illustrated the further validation of network lifetime efficiency of the presented model; a comparison analysis is demonstrated with the previous method by means of stability period, half node die (HND) as well as network lif

Fig. 4 illustrates the analysis of the presented model with existing methods under varying node count interms of number of packets. The figure depicted that the proposed method has achieved a higher number of packets under varying number of nodes. At the same time, the MGWO-LF and IPSO-DV algorithms have attained a slightly lower number of packets. Likewise, the HPSOGWO and FBECS algorithms have reached a minimum number of packets.

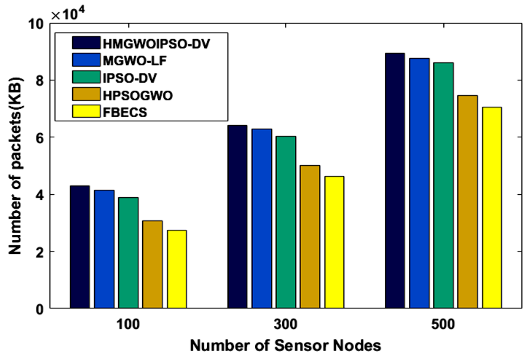

Fig. 4: Comparative results analysis of proposed and existing methods in terms of number of packets transmitted

CONCLUSION

This paper has developed an effective hybrid clustering technique called HMGWOIPSO-DV algorithm. The presented algorithm involves CH selection in two levels namely IPSO-DV based tentative CH selection and MGWO based final CH selection. Besides, the presented model derived a fitness function by the use of residual energy, distance to BS, and distance to nearby nodes. The proposed model has the capability of competently choosing the CHs, attains energy efficiency, and maximum network lifetime. A series of experiments were carried out to ensure the energy efficient performance of the projected model. The inclusion of two algorithms for CH selection leads to the optimal CH selection and thereby network lifetime gets improved. The obtained simulation outcome ensured that the proposed model has outperformed the compared methods in a significant way. In future, the proposed model can be extended to the use of data aggregation techniques to reduce the quantity of data transmission in WSN.

CONFLICT OF INTEREST

There is no conflict of interest.

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FINANCIAL DISCLOSURE

None.

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