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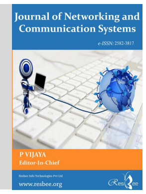

Hybrid GSDE: Hybrid Grasshopper Self Adaptive Differential Evolution Algorithm for Energy-Aware Routing in WSN

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Abstract: In the sectors of the military, healthcare, and weather monitoring the Wireless Sensor Network (WSN) has extensive applications. The effectual model of the WSN needs enhanced energy optimization approaches because the nodes in the WSN are battery operated. The conventional energy-aware routing schemes abandon the traffic rate and delay of the WSN when enhancing the constraints of the energy in the node. By adopting a multi-objective energy-aware routing protocol this article succeeds in dealing with these challenges. Moreover, this work presents the multi-objective fitness model based on the density of the cluster, energy, traffic rate, delay, and distance. On the basis of the proposed Hybrid Grasshopper Self adaptive Differential Evolution (HGSDE) Algorithm, the energy-aware routing is performed. In the WSN, the presented HGSDE algorithm is used to find the optimal Cluster Head from several Cluster Head Nodes. Subsequently, the optimal routing path is demonstrated on the basis of the proposed multiobjective function. Finally, the proposed method is compared with the conventional methods such as Particle Swarm Optimization (PSO), Differential Evolution (DE), and Artificial Bee Colony (ABC). The overall analysis states that the performance of the proposed method is better than the conventional methods.

Keywords: WSN; Energy-Aware Protocol; Delay; Alive Nodes; Network Energy

Nomenclature

Abbreviations	Descriptions
WSN	Wireless Sensor Networks
EH	Energy- Harvesting
BS	Base Stations
MTE	Minimum Transmission Energy
RF	Radio Frequency
PEGASIS	“Power-Efficient Gathering in Sensor Information Systems”
SG	Smart Grid
SCs	Smart Cities
ODGRP	Reliable Data Gathering Routing Protocol
IoT	Internet of Things
SEMCL	SEMantic CLustering
REWLS	Robust and Efficient Weighted Least Square method
QoS	Quality of Service
TOD	True Outlier Detection
CH	Cluster Head
IEA	Intermittent Energy-Aware
CHN	Cluster Head Nodes
ETC	Expected Transmission Count
EAI	Energy-Aware Interface
LEACH	Low Energy Adaptive Clustering Hierarchical
SH	Sensor Head

1. Introduction

Generally, WSNs considered as an intelligent and refined model for distinctive discernible devices, which are competent and wirelessly interface with each other using the Internet [1]. WSN is gathered with SNs, which are exploited to monitor large aspects such as vibration, temperature, sound, humidity, pressure, so forth. In WSN, the most important applications are to compute several factors of the environmental, which affects the weather circumstances. The restricted or considerable failures in WSN

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occur due to the specific weather circumstances. For instance, when few environmental factors such as humidity and temperature may affect the strength of the received signal as well as the quality connection of a WSN, in a large geographical region, a dreadful weather circumstance such as natural disaster might eventually unbalance the working of WSN. These events might hamper the day-to-day practice of society, which extremely depends on WSNs for its several pivotal enterprises. Because of the changes in weather circumstances are assumed to occur as well as the probability of incoming calamities weather is highly time-deviating, it is important to estimate the factors of environmental in a systematic short time interval. Moreover, it is important to transmit these measurements to the BS or network operator hence that actual efforts could be taken over the forthcoming disastrous weather before it hits. In an energy-constrained WSN, transmitting all the measurements to the BS is unenviable as it instigates a huge amount of energy utilization [10].

In WSN, to expand the network lifetime, EH techniques are extensively exploited [21] [22]. Moreover, the EH-WSN has the ability to gather environmental energy, like, RF, light and wind energy that is subsequently changed into electrical energy and saved for WSN nodes [23]. The WSN energy is mostly saved in rechargeable capacitors or batteries. The rechargeable battery-powered WSN nodes possess adequate energy with maximum energy density, to work in a way as same as that of a conventional WSN as the networking protocol and methods are examined adequately [11] [12].

The condemnatory fault reclines such as in the charge revolution times are restricted, as well as the rechargeable battery needs the number of energy for charging. If the node loses power, it requires extensive time to wake up or it does not have the ability to start again that tends to unbearable delay in the network as well as limits the lifetime of the network solemnly. A compact capacitor merely requires less number of energy to charge with a comparatively maximum voltage, hence attaining shorter network delay and maximum unrestricted lifetime comparing with the conventional technique [13] [14] [15].

Various protocols were presented in the state of the arts with the objective of prolonging the lifetime of the sensor network using the cluster-based network architectures. In [7], one of the renowned clustering protocols named LEACH was developed. Generally, LEACH is represented as a cluster-based protocol, which comprises distributed cluster configuration in that the nodes with some probability choose themselves as CH. Moreover, LEACH offers adequate energy savings and an extended lifetime for the network against the traditional multihop routing methods like the MTE routing protocol [7]. On the other hand, it does not assure that the preferred number of CHs is chosen and CHs are not consistently located over the network. An additional clustering protocol that aspires to enhance the network lifetime is developed in [8]. To systematize nodes into a sequence PEGASIS exploits a greedy approach, hence that each node sends and receives from only one of its neighbors. The function of the PSO technique to resolve the issue in sensor network clustering was presented in [9]. In each cluster to balance the number of nodes and candidate CHs to reduce the energy exhausted by the nodes when increasing the transmission of data transmission was attempted in [9]. Nevertheless, no evaluation with other standard clustering protocols regarding the effectiveness of energy was addressed in [9].

The major contribution of this paper is to design the Hybrid GSDE technique in order to discover the optimal CHN in the WSN and also to present the energy-aware routing. Initially, the multi-objective fitness function is described on the basis of the several features of the nodes, namely distance among the nodes, delay, traffic rate, cluster density, as well as the energy of the nodes. Subsequently, the routing is performed using the proposed Hybrid GSDE algorithm. The proposed method is the hybridization of the Grasshopper Optimization algorithm with the self-adaptive Differential Evolution Algorithm.

2. Literature Review

In 2019, M. Faheem et al. [1], worked on a smart grid, which was a prominent idea, which developed a novel scheme to handle the quality of the power and consistency problems for both service consumers and providers. The main objective of the SG in SCs was to maintain a particular amount of residents' life quality and assist the complete spectrum for their economic activities. Here, a novel Energy Efficient and ODGRP were presented for WSNs on the basis of the smart grid applications. In the SG, the proposed method uses multiple mobile sinks for energy effectual and a software-defined centralized controller and as well as consistent data gathering from WSNs.

In 2019, Shishupal Kumar et al. [2], worked on IoT, it offers maximum scalability using the assistance of the huge number of Internet users with the practice of IPv6 in place of IPv4. Moreover, it was important that the operational protocol and modules should be energy effectual. The main cause was the existence of an installed sensor is openly associated with its instant battery draining. Considering aforesaid points several protocols were exploited and examined by IoT on the basis of the WSN.

In 2019, Srijit Chowdhury et al. [3] presented an energy effectual SEMCL model in order to alleviate the maximum energy utilization issue in a clustered WSN. This model creates energy effectual clusters using sturdy intra-cluster data resemblance to use spatial correlation of data. Hence, the REWLS was adopted to offer precise data prediction with insignificant errors. Due to REWLS technique require differentiate false and true outliers and hence to enhance additional the QoS on data accurateness, a separate technique, called TOD.

In 2018, Yang Zhang et al. [4], developed a general IEA EH-WSN platform a double-phase capacitor model to assure node synchronization in circumstances without energy-yielding was adopted. Additionally, an integrator was exploited to attain ultra-low-power measurement. While considering the software and hardware, an optimized energy managing strategy was provided for irregular performance. Moreover, the complete model of the IEA platform and detailed the energy managing scheme from the features of energy measurement, energy management, and energy prediction was described. Additionally, they have attained node synchronization in different time in addition to measure the energy in reality, energy environments, as well as presented the lightweight energy computation technique on the basis of the measured solar energy.

In 2018, Tingwen Ruan et al [5], developed a combined EAI with an energy-aware plan in order to contract with the disparity by controlling the energy flow from the energy storage capacitor to the WSNs. Moreover, these integrated energy-aware techniques were employed and experimentally examined in a custom developed piezoelectric vibration energy harvesting powered WSN. These techniques were exploited in a custom exploited vibration energy-yielding powered WSN.

In 2019, Oluwatosin Ahmed Amodu and Raja Azlina Raja Mahmood [6], proposed a LEACH routing protocol to extend the lifetime of the SNs by partitioning the network into clusters. A CHN receives and comprehensive data from other nodes in each cluster. On the other hand, CH nodes in LEACH were arbitrarily selected that tends to a speedy loss of network energy. It happens while the CH has a minimum energy level or while it was distant from the BS. LEACH with two-level CH (LEACH-TLCH) protocol positions a secondary CH (2CH) to alleviate the CH encumber in these situations.

3. Network model of WSN

3.1 WSN Model

In fig. 1, the WSN model is demonstrated, and WSN consists of N number of SNs. In the WSN, each node is separated by the maximum distance, and the sensor node communicates with each other by the prescribed radio range. In the WSN, $\mathrm{SN_i}$ indicate the sensor nodes, and the value of i ranges among $1 \le \mathrm{i} \le \mathrm{N}$. The WSN dimension is represented as (L, M) in meters, the $\mathrm{SN_i}$ in the WSN transfer information with each other by the wireless medium. The nodes transmit the sensor readings to the BS, which is represented as $\mathrm{B_S}$ and the position of the $\mathrm{B_S}$ in the WSN is indicated as $\{0.5\mathrm{L_i}, 0.5\mathrm{M_i}\}$. With the aid of the optimal local minimal value, the position of the $\mathrm{B_S}$ in the WSN is selected. The position of the each $\mathrm{SN_i}$ in the WSN is represented as $\{\mathrm{L_i}, \mathrm{M_i}\}$.While each node transmits their information to the $\mathrm{B_S}$ node, congestion happens in the WSN and the nodes transmit the sensor readings to the CH. Moreover, the CHN ($\mathrm{HN_j}$) transmit information with the $\mathrm{B_S}$. Additionally, the WSN comprises $\mathrm{N_n}$ number of $\mathrm{H_j}$, and j deviates among $1 \le \mathrm{j} \le \mathrm{N_n}$. A total number of the standard nodes in the WSN is the difference in the total number of SN and the total number of HN_j nodes that is $(\mathrm{N} - \mathrm{N_n})$. The standard SN in the WSN transfer information with the $\mathrm{B_S}$ by its equivalent $\mathrm{HN_j}$. The chosen of the $\mathrm{HN_j}$ in the cluster is the optimization issue.

The nodes energy represented as an important model for the effectual WSN routing. In the WSN, each node represented as a battery-powered and the SN_i preserves a routing table. The data contains in the routing table causes random changes during the process of the routing, so the minimization of the energy occurs in the nodes. During the initial stage, $\mathrm{ER_{initial}}$ is represented as the initial energy on SN_i, and the node energy residue as maximum. The node energy gets minimized subsequent to the routing procedure however; the node energy cannot be rechargeable. Receiving and transmitting packets to SN_i minimizing energy. By exploiting the radio model, the residue energy in each node of the WSN can be designed. Generally, the WSN comprises both the sender node as well as the receiver node. The receiver and the sender posses the power amplifier and radio electronics. In the WSN, each broadcast and reception of the data packets, the nodes energy gets dissipation. While the distance among $\mathrm{SN_i}$ and the

HN_j is higher than the initial distance $ds_{initial}$, subsequently the energy dissipation of the node SN_i is stated in eq. (1).

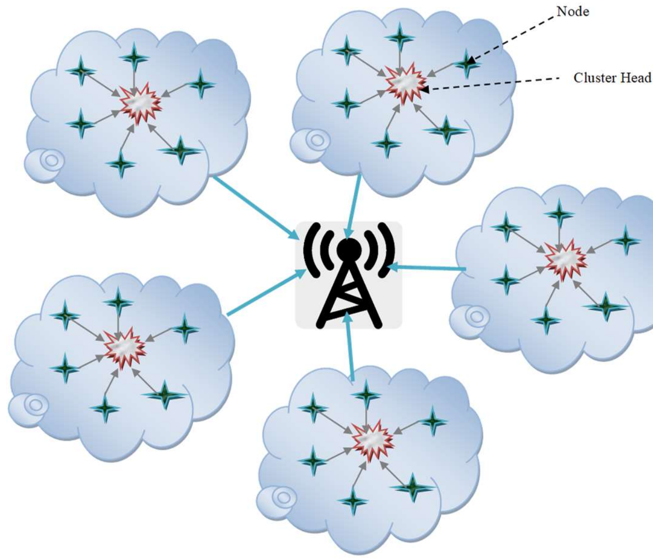

Fig. 1. System model of WSN

$$ER_{dissipation}(SN_i) = ER_{elec} * sp + ER_{amp} * sp + \left\| SN_i - HN_j \right\|^4 \tag{1}$$

In eq. (1), sp indicates the packet size, HN_j indicates the CHNs in the WSN and SN_i indicates the SNs in the WSN. While the distance among SN_i and HN_j is smaller than the initial distance $ds_{initial}$, subsequently the energy dissipation of the node SN_i is stated in eq. (2).

$$ER_{dissipation}(SN_i) = ER_{elec} * m + ER_{fs} * sp + \left\| SN_i - HN_j \right\|^2 \tag{2}$$

In eq. (2), the variable ER_{fs} represents the receiver node sensitivity. Eq. (3) states the energy dissipation because of the initial distance among the node and the HN_j.

$$ER_{ds\,initial} = \sqrt{\frac{ER_{fs}}{ER_{amp}}} \tag{3}$$

In eq. (3), the ER_{fs} represents the receiver node sensitivity, the ER_{elec} represents the electronic energy of the WSN, and the ER_{amp} represents the noise figure of the amplifier. The ER_{elec} represents the electronic energy, which describes the energy, dissipated in the node because of the factors, namely spreading, amplification, filtering, modulation, and coding. The eq. (4) describes the electronic energy of the network.

$$ER_{elec} = ER_{TX} + ER_{DA} \tag{4}$$

In eq. (4), ER_{DA} denote the data aggregation energy and ER_{TX} indicates the transmitter energy. At the CH, the energy dissipation happens because of the data transmission to B_S as well as because of the receiving data from SN_i. The eq. (5) represents the energy dissipated at HN_j.

$$ER_{dissipation}(HN_j) = ER_{elec} * sp \tag{5}$$

The data on the network is further transmitted and received by the nodes. This reduces the remaining energy on the nodes. The eq. (6) and (7) represents the energy equation of SN_i and HN_j are updated.

$$ER_{t+1}(SN_i) = ER_t(SN_i) - ER_{dissipation}(SN_i) \tag{6}$$

$$ER_{t+1}(HN_j) = ER_t(HN_j) - ER_{dissipation}(HN_j) \tag{7}$$

In eq. (7), the variable $ER_t(SN_i)$ denotes the energy of the node at the time t, the variable $ER_{t+1}(SN_i)$ denotes the updated energy at SN_i, and the variable $ER_{dissipation}(SN_i)$ denotes the dissipated energy of SN_i. The variable $ER_{t+1}(HN_j)$ denotes the updated energy at HN_j, the variable $ER_t(HN_j)$ denotes the energy of HN_j at the time t, and the variable $ER_{dissipation}(HN_j)$ denotes the dissipated energy of HN_j.

3.2 Multi-objective Fitness Model

In this work, the selection of CHNs from the SNs in the WSN based on the presented Multi-objective Fitness model. Moreover, this work presents the maximum fitness function on the basis of the several objectives, like distance, traffic rate of the nodes, delay, density within the cluster, and the energy of the nodes. In order to choose the SN as the CH, each node fulfills the fitness model offering the maximum value. The proposed Multi-objective Fitness function is represented in eq. (8).

$$\underset{max}{Fitness} = \left\{\left[1-\frac{D_L(t)}{D_{Lnorm}}\right]+\left[1-\frac{P(t)}{Y*N_n*N}\right]+\left[ER(t)\right]+\left[1-TR(t)\right]+\left[1-W(t)\right]\right\} \tag{8}$$

In eq. (8), $D_{L_{norm}}$ denotes the normalized delay of the WSN and $D_L(t)$ denotes the delay of the SNs in the WSN. $P(t)$ denotes the distance among the CHNs and the SNs, N_n denotes the total number of the CHs in the WSN, Y denotes the total number of nodes in the cluster, N denotes the total number of nodes in the WSN. $TR(t)$ denotes the rate of the traffic nodes nearby the cluster, $ER(t)$ denotes the CHN energy. $W(t)$ denotes the density of the clusters in the WSN. The multi-objectives of the fitness function is described below:

(a)Delay:

In each node of the WSN, delay in the WSN states the sum of the delay occurs. To choose the node as the CH, the delay must be as low as potential. The node delay directly based upon the ETC of the node, transmission network delay, and propagation node delay. In the WSN, the eq. (9) states the delay of the node.

$$D_L(t) = \sum_{i=1}^{N} K_i(t)(\delta + \gamma_i) \tag{9}$$

In eq. (9), $K_i(t)$ denotes the ETC of the i^{th} node of the WSN at the time t, γ_i denotes the propagation delay of the i^{th} node of the WSN and δ denotes the transmission delay of the network. The node ETC based on the ratio of the received delivery packet and the ratio of the forward delivery packet of the node at a time t. The eq. (10) indicates the ETC of the i^{th} node of the WSN.

$$J_i(t) = \frac{1}{FW_i(t) * RP_i(t)} \tag{10}$$

In eq. (10), $RP_i(t)$ and $FW_i(t)$ denotes the received and ratio of the forward delivery packet the i^{th} node at a time t.

(b) Distance:

The distance is considered as the second objective fitness function, which represents the distance among the cluster heads and the nodes. The distance among the cluster heads and the nodes must be less for the effectual communication. In eq. (11), the distance between the cluster heads and the nodes are represented, where nodes that belong to the j^{th} cluster are obtained for the distance measure.

$$D(t) = \sum_{j=1}^{N_N} \sum_{i=1}^{N} \left\| SN_i - HN_j \right\|; \qquad \vee j \in i \tag{11}$$

(c)Energy:

The nodes energy must be higher to choose the node as the CH. Eq. (12) represents the energy of the CHs in the WSN.

$$ER(t) = \frac{1}{N_n} \sum_{j=1}^{N_n} ER_{t+1}(HN_j) \tag{12}$$

In eq. (12), $ER_{t+1}(HN_j)$ denotes the updated energy of the CH and the value is attained from the eq. (7).

(d)Density:

For enhanced communication among the nodes, the density of the nodes within the cluster must be less. The rise in density within the cluster raises the packet drop and congestion. The node density describes the number of nodes ratio within the cluster to the total number of nodes in the WSN. The density of the cluster in the WSN is represented in eq. (13), $|Y_j|$ denotes the nodes in the j^{th} cluster.

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$$W(t) = \frac{1}{N} \sum_{j=1}^{N_n} |Y_j| \tag{13}$$

(e)Traffic rate:

For the derivation of the fitness function, the final objective needed is the traffic rate of the cluster. It contains less value for the enhanced communication procedure and it ultra-low-power in eq. (14), $FL_i(t)$ denotes the flow rate of the i^{th} node.

$$\text{Traffic rate,} \quad TR(t) = \sum_{i=1}^{N} \frac{FL_i(t)}{\max FL_i(t)} \tag{14}$$

4. Optimized Cluster head selection Using Proposed model

4.1 Conventional Grasshopper Optimization Algorithm (GOA)

GOA is enthused by the swarming behavior of grasshoppers in nature [16]. In this algorithm, three important features, that influences the grasshopper individual movement such as gravity force, social interaction, and wind advection [17], [18]. The eq. (15) represents the mathematical model of their swarm behavior.

$$Y_i = I_i + F_i + W_i \tag{15}$$

In eq. (15), Y_i represents the location of the i^{th} grasshopper. F_i represents the gravity force, I_i represents the social interaction, and W_i represents the wind advection on the i^{th} grasshopper, correspondingly. Nevertheless, eq. (15) cannot be directly exploited to resolve optimization issues. Hence, the modified version is stated in eq. (16).

$$Y_i^d = s\left(\sum_{j=1\, j\neq 1}^{N} s\,\frac{v_d - l_d}{2}\, c\left(\left|y_j^d - y_i^d\right|\right)\frac{y_j - y_i}{d_{ij}}\right) + \hat{B}_d \tag{16}$$

In eq. (16), l_d indicate the lower bound and v_d indicate the upper bound on the d^{th} dimension, correspondingly. $\hat{B}_d$ denotes d^{th} dimension value in the optimal solution attained hitherto. $d_{ij} = y_j - y_i$ indicates the distance among the i^{th} grasshopper and j^{th} grasshopper. c indicate a designed model which is computed using $c(s) = fe^{-s/l} - e^{-s}$, where, f and l are two constants. s represents an important parameter of conventional Grasshopper Optimization Algorithm, which can balance the exploitation and exploration of optimization. It minimizes with the number of iterations and computed as eq. (17).

$$s = s_{max} - t\,\frac{s_{max} - s_{min}}{t_{max}} \tag{17}$$

In eq. (17), t indicates the current iteration, s_{max} represents the utmost values and s_{min} represents the minimum values, correspondingly, and t_{max} represents the utmost number of iterations.

4.2 Conventional Differential Evolution (DE) Algorithm

DE algorithm is represented as an easy and influential evolutionary algorithm that has attracted wide concentration against the last few decades [19]. In this algorithm, three important operators are exploited such as mutation, crossover, and selection. Scaling factor S_F and crossover probability cr are considered as two important parameters that influence the exploitation and exploration and stages of optimization.

a) Mutation

In the DE algorithm, the mutation operator is computed as eq. (18). Here, M_i^{t+1} denote the mutant individual in the $(t+1)^{th}$ iteration. $y_{r_1}^t$, $y_{r_2}^t$, and $y_{r_3}^t$ denote three different individuals in the population. In particular, r_1, r_2, and r_3 are not equal. S_F represents the scaling factor, which is constant.

$$M_i^{t+1} = y_{r_1}^t + S_F \times \left(y_{r_2}^t - y_{r_3}^t\right) \tag{18}$$

b) Crossover

Subsequent to the procedure of mutation, from the mutant individual M_i^{t+1} or the current individual y_i^t the trial individual C_i^{t+1} is selected with the reason of enhancing the population diversity. The eq. (19), states the crossover operation of the DE algorithm.

$$C_i^{t+1} = \begin{cases} M_i^{t+1} & \text{if } r \le cr \\ y_i^t & \text{if } r > cr \end{cases} \tag{19}$$

In eq. (19), cr is a constant that indicates the crossover probability and r represents a uniformly distributed arbitrary number in the interval [0, 1].

c) Selection

A comparison among the trial individual C_i^{t+1} and the current individual y_i^t during the selection procedure is done to attain an individual of $(t+1)^{th}$ generation. The selection operation is stated in eq. (20) for a minimization issue, here w f denotes the objective model of the given optimization issue.

$$y_i^{t+1} = \begin{cases} C_i^{t+1} & \text{if } f\left(C_i^{t+1}\right) < f\left(y_i^t\right) \\ y_i^t & \text{O.W} \end{cases} \tag{20}$$

4.3 Self-Adaptive Differential Evolution Algorithm (SDE)

In conventional DE algorithm, these two control parameters are constant by the complete evolutionary procedure. Nevertheless, the fixed value cannot become accustomed well to several issues, particularly in complex high-dimensional issues.

Hence, an enhanced version of DE was introduced in [20], which have the ability to set the control parameters adaptively. In the enhanced DE, S_F indicates the control parameters and c_r is stated in eq. (21) and (22).

$$S_{F_i}^{t+1} = \begin{cases} S_{F_l} + r_1 \times S_{F_v} & \text{if } r_2 < \sigma_1 \\ S_{F_i}^{t} & \text{O.W} \end{cases} \tag{21}$$

$$c_{r_i}^{t+1} = \begin{cases} r_3 & \text{if } r_4 < \sigma_2 \\ c_{r_i}^{t} & \text{O.W} \end{cases} \tag{22}$$

In eq. (21) and (22), σ_1 and σ_2 indicate the transition probability, which is set to 0.1. S_{F_l} and S_{F_v} represents the scaling factor bound. The initial value of c_r and S_F are set to 0.9 and 0.5, correspondingly that can aid the method to attain a notable performance. Each search agent has its own S_F and c_r, which is found in eq. (21) and (22). The two parameters value might vary; however, the transition probability indicated by σ is less during the iteration process. That is to say, the value of the parameter for each search agent is suitable in various scenarios when the value will also become arbitrary to maximize the diversity of the population.

4.4 Proposed HGSDE Algorithm

The proposed algorithm finds the optimal routing path for the routing process. The algorithm finds the optimal cluster head between the several cluster heads in the WSN. Hence, the conventional GOA method is hybridized with self-adaptive DE algorithm to enhance the efficiency of the search when maintaining population diversity, particularly in the later on iterations in this paper. In the proposed approach, it is significant the DE method act as a local search scheme. Nevertheless, that its exploration ability can be discarded or yet ignored. Subsequent to all, a better balance among exploitation and exploration, this is vital for the meta-heuristic technique, yet as an element of a hybrid technique. Hence, an enhanced version of DE is exploited as an alternative of the conventional DE.

In the proposed method, a simple and efficient hybrid method is introduced to improve the optimization capability without maximizing the computational complexity. In the current generation, the average objective value of the population indicates the complete quality of the search agents. The value of fitness function for an individual must be minimum than the average for a problem, which needs to be minimized, it represents the nearby search area of the particle is possible and shows potential. Hence, a scheme to improve the local search must be exploited. Conversely, if the fitness function value is higher than the average value, the local search scheme will not be exploited. Moreover, the adoption of self-adaptive DE will not create the method in advance converge due to the scaling difference among individuals creates the population more arbitrarily distributed. This feature can enhance preserve the diversity of populations, particularly in the behind evolution procedure. Fig 2 states the schematic diagram the proposed hybrid GSDE technique.

Algorithm: Pseudo code of the proposed Hybrid GSDE algorithm		
In the search space; initialize a randomly distributed population		
Initialize the optimal search agent $\hat{B}_d$;		
Initialize the fitness values of the grasshoppers f_i;		
Set as population size N and maximum number of iterations t_{max};		
Set the dimensions of the optimization problem dim, the number of thresholds;		
while (termination condition is not met ($t > t_{max}$)		
By eq. (8), evaluate the $Fitness_{max}$ value		
Update the position $\hat{B}_d$ and fitness value of optimal search agent if there is an enhanced one;		
By eq. (17), evaluate the parameter s		
Calculate the average ($Fitness_{max}$)fitness value of the population;		
	for each grasshopper $(i = 1 : n)$	
		if $(f_i > f)$% GOA
		By eq. (16) update the location of grasshopper
		else Self-adaptive DE operator
		By eq. (21) and (22), for each search agent evaluate S_F and c_r
		By eq. (18), (19) and (20) perform mutation, crossover, and selection operators
		end if
	end for	
end while		

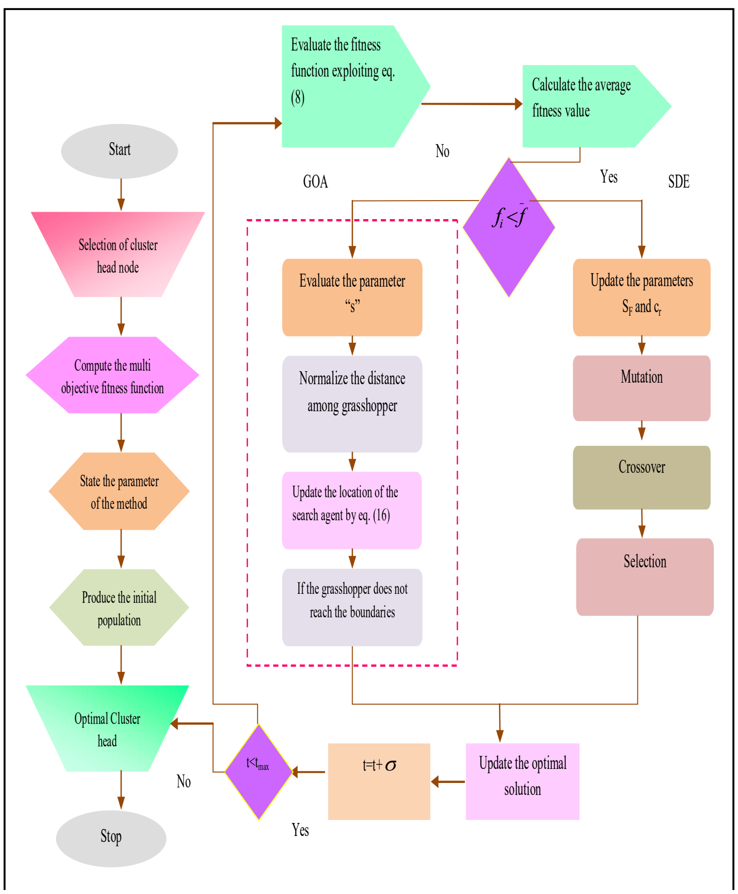

Fig. 2. *Schematic diagram of the proposed Hybrid GSDE technique*

5. Results and Discussions

5.1 Experimental Procedure

This section exhibits the simulation procedure of the proposed Hybrid GSDE method. Moreover, the proposed method was compared with conventional algorithms such as PSO, DE, and ABC algorithms. Here, the metrics like normalized network energy and number of alive nodes were exploited to examine the performance of the proposed method. Table 1 summarized the simulation parameters of the WSN.

Table 1: *Simulation parameters of the WSN*

Parameters	Values
X and Y dimension	100
Initial energy of the node	0.5
Noise figure of the amplifier	0.0013 pJ/bit/m^2
Bit rate	4000 bit
Number of nodes	50, 75, 100
Sensitivity of the receiver	10 pJ/bit/m^2
Data aggregation energy	10 nJ/bit/signal
Energy required for the transmission	50 nJ/bit/m^2

5.2 Performance Analysis in Terms of Number of Alive Nodes

Fig 3 exhibits the performance evaluation of the proposed technique with the conventional techniques regarding the number of alive nodes. Here, the analysis is performed by varying the number of iterations. Moreover, the performance analysis has been evaluated for 50 nodes. Here, the proposed method is 21% better than the PSO, 22% better than the ABC and 25% better than the DE algorithm. Moreover, when comparing with the conventional algorithms, the proposed method posses a huge number of alive nodes. Fig. 4 depicts the evaluation of the proposed technique over the conventional techniques with respect to the number of alive nodes for 100 nodes. Here, the proposed method is11% superior to the PSO, 15% superior to the ABC and 16% superior to the DE algorithm.

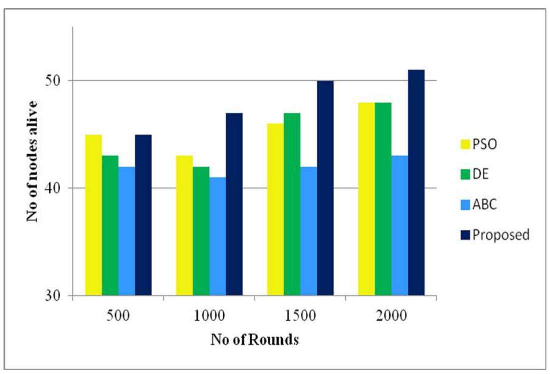

Fig. 3. Graphical representation of the proposed technique regarding the number of alive nodes for 50 nodes

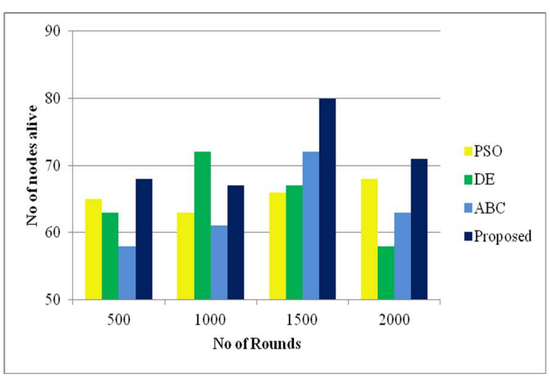

Fig. 4. *Graphical representation of the proposed technique regarding the number of alive nodes for 100 nodes*

5.3 Performance Analysis Regarding Normalized Network Energy

Fig 5 and 6 demonstrated the performance analysis of the proposed technique and conventional techniques for the normalized network energy. Moreover, the proposed method has been evaluated for 50 nodes, which is shown in Fig 5 and 100 nodes in Fig 6. In Fig 5, the proposed method is26% superior to the PSO, 28% superior to the ABC and 31% superior to the DE algorithm for 50 nodes. In Fig 6, the proposed method is16% superior to the PSO, 21% superior to the ABC and 25% superior to the DE algorithm. The overall analysis of both Fig 5 and 6 shows the normalized energy of the proposed technique is higher while comparing with the conventional algorithms.

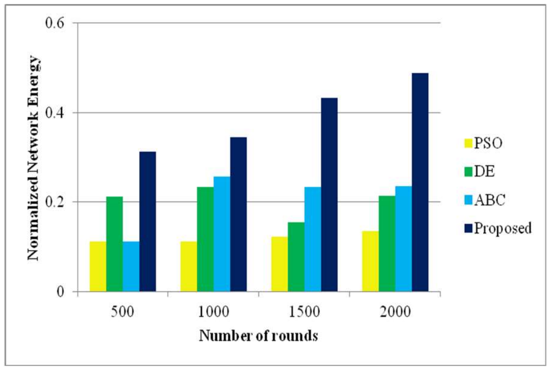

Fig. 5. *Graphical representation of the proposed method with respect to the normalized network energy for 50 nodes*

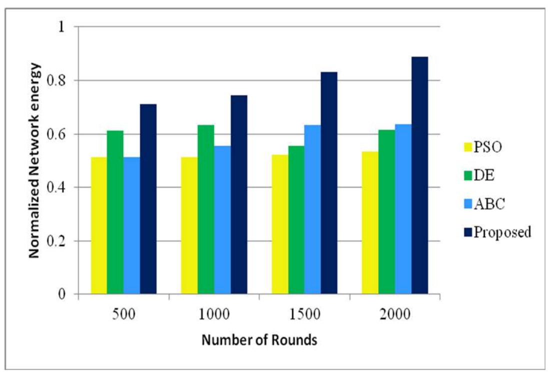

Fig. 6. *Graphical representation of the proposed technique regarding the normalized network energy for 100 nodes*

6. Conclusion

Generally, energy efficiency has been recognized as the one of the most important issue in all facets of the WSN operations. In the WSN, it was essential to employ sub-optimal paths occasionally to augment the survivability of networks for energy-aware routing scheme. In this paper, an energy-aware routing scheme for the WSN was introduced. Moreover, this work proposed the Hybrid GSDE algorithm, which was exploited by the multi-objective fitness model in order to choose the optimal CH for the routing procedure. The proposed method comprises several factors like delay, energy, traffic rate, distance, and the density of the nodes to calculate the fitness function. At last, the performance analysis of the proposed with conventional techniques namely DE, ABC, and PSO was performed. SO, the metrics, like normalized network energy and a number of alive nodes compute the performance of the methods.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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