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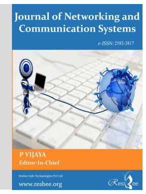

Multi-objective HSDE Algorithm for Energy-Aware Cluster Head Selection in WSN

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Abstract: From a remote area for collecting and sensing the data of an environment, the Wireless Sensor Networks (WSNs) are extensively used and also it is exploited for a variety of engineering applications. The routing protocols are exploited in order to transfer the data among the nodes is enabled which face enormous challenge regarding energy. By means of the optimal cluster head selection process, the energy-aware routing is presented with energy as an effective constraint. The proposed algorithm of choosing the optimal Cluster Head (CH) is done by exploiting the Multi-Objective Harmony Search Differential Evolution (MHSDE) method which is the integration of the Harmony Search (HS) and the Differential Evolution (DE). The proposed objective model is on the basis of the distance among the nodes in the cluster, traffic density of the cluster, energy of the nodes, and the delay in transmitting the data packets. The proposed objective model is adjusted to a less value and the CH similar to the less value of the objective mode becomes the optimal CH. In the WSN environment, the experimentation is performed by taking into consideration of 50 nodes for analysis.

Keywords: WSN; Cluster; Cluster Head Selection; Alive Nodes; Energy; Throughput

Nomenclature

Abbreviations	Descriptions
LEACH	Low-Energy Adaptive Clustering Hierarchy
WSN	Wireless Sensor Network
BS	Base Station
SN	Sensor Nodes
TEEN	Threshold-sensitive Energy Efficient sensor Network
GSO	Group Search Optimization
APTEEN	Adaptive Periodic Threshold-sensitive Energy Efficient Network
ABC	Artificial Bee Colony
EA-DB-CRP	Energy-Aware And Density-Based Clustering and Routing Protocol
PSO	Particle Swarm Optimization
FCM	Fuzzy C-Means
CSS	Cooperative Spectrum Sensing
IoT	Internet of Things
PSNs	Public Safety Networks
GGWSO	Grouped Grey Wolf Search Optimisation
MCDM	Multi-Criteria Decision Making
CMIMO	Cooperative Multiple-input-multiple-output
CHESS-PC	Cluster-Head Selection Scheme with Power Control
MIMO	Multi-Input Multi-Output
GWO	Grey Wolf Optimization
QPSO	Quantum-Inspired Particle Swarm Optimization

1. Introduction

The advancements of recent technologies create the WSN appropriate in both technical and economic circumstances. A distribution system that comprises a few SN and BS is referred to as the WSN [1]. The SN can sense the surrounding environments with respect to the light, speed, temperature, pressure, and change in displacement and so forth. Hence, these nodes have the advantage of presenting appropriate wireless communication and micro-sensing. In diverse applications, WSN can be exploited with specific aforesaid characteristics. In the network, each node directly communicates with the BS during the distribution of data. Since the transmission of data persists, the node with more distance expires faster

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than the other nodes by losing their energy. For that reason, the clustering process is exploited, which collects the nodes in the form of a variety of clusters to resolve this problem [2]. Using the clustering process, the broad network performance is considered resolved, with many nodes [17]. Additionally, the network reduces the obligation of the central organization and motivates the local decisions, which in order improves the scalability. From the active network, the clusters retrieve data using the clustering process. In addition, for each cluster, an appropriate cluster head must be selected which obtains data from the SNs and transmits to the BS. A few restrictions of WSN comprise less adaptation, life expectation, and maximum energy utilization, network with large scale, and extra overhead and energy coverage [3].

In general and in accordance with the WSN model, routing protocols can be categorized as hierarchical based, flat-based, and location-based protocols. Because of the nature of nodes and their sturdiness, cluster-based routing protocols are the general model exploited in WSNs. In these protocols, SN is collected into clusters whereas every cluster comprises of cluster head and normal nodes [16]. Generally, the cluster head is selected along with a few definite criterions that frequently allow for memory, energy, and bandwidth of SNs. It is mostly in charge of gathering data from its members, combined it, and eventually relaying it to the BS. Cluster heads, nearest to the BS, be inclined to tire their power higher than others due to their additional chore of relaying data traffic to the BS. Enchantingly, if the energy utilization is even between all sensors which are uniformly distributed, subsequently the energy hole is turned away and the lifetime of the network is enhanced. Hence, presenting protocols that aim at increasing the lifetime of the network is enormously difficult [4].

Numerous clustering algorithms were exploited in WSN and been able to create the network power-competent. LEACH [12] is a decentralized clustering algorithm with a two-hop topology. For a cluster, a node is arbitrarily chosen as CH in LEACH. In the network, it does not assurance the uniform distribution of CHs. On the other hand, it enhances the lifetime of the network when comparing with the least-transmission-energy or direct communication algorithm; also named a non-clustering based algorithm. An improvement in LEACH works as same as the conventional LEACH however in a centralized model. Further clustering algorithms on the basis of the LEACH are Power-Efficient Gathering in Sensor Information method, APTEEN [13], the TEEN [14], and Hybrid Energy-Efficient Distributed [15] protocols. These algorithms do improve the lifetime of the network by enhancing network effectiveness; however, they do not optimize the formation of the cluster.

The main objective of this paper is to present an MHSDE method. This method is to present the MHSDE method, which is the combination of the Harmony Search and Differential Evolution. Here, the best objective of MHSDE algorithm is to choose the optimal CH by exploiting multiple objectives, like energy, distance, traffic density, and delay. Moreover, the objective model is to be in the least amount for the proposed model guarantees the minimization of parameters like energy, distance, delay, and traffic density.

2. Literature Review

In 2019, Abdul Rahim Ansari et al [1], worked on wireless network technologies, which had experiences inspiring notice from PSNs and Public Safety Communications. WSN comprises of battery-operated nodes to suspiciously concentrate on the power utilization of the network, which was an important problem. In wireless networks, numerous clustering algorithms had exploited to undertake the power utilization problem and they had exhibited electrifying results. Beside different clustering algorithms, suitable CH chosen plays a vital role in creating wireless networks additional power-competent. On the other hand, clustering was not implemented in PSNs in conventional investigations. Here, a clustering-based CHESS-PC was proposed for PSN. Additionally, it exploits FCM as a clustering tool.

In 2019, Trupti Mayee Behera et al [2], worked on WSN groups particular transducers that present sensing services to IoT devices with storage resources and inadequate energy. As recharging or replacement of batteries in SN was approximately not possible, power utilization considered as the critical design problem in WSN. For the energy-constrained network, the clustering method plays a significant role in power conservation. Selecting a CH can suitably balance the load in the network thus minimizing energy utilization and improving lifetime. Moreover, this work concentrates on a competent CHS method which rotates the CH location between the nodes with superior energy levels as evaluated with others. The method comprises primary energy, remaining energy and the best value of CHs to select the subsequent group of CHs for the network which ensembles for IoT applications like smart cities, environmental monitoring, and systems.

In 2019, S. Murugaanandam and Velappa Ganapathy [3], developed an algorithm like reliability-based enhanced technique for the ordering of preference by similarity ideal solution (RE-TOPSIS) integrating with fuzzy logic that exploits MCDM algorithm helping in the effectual and consistent CH

Selection. Additionally, it exploits the existing LEACH protocol to facilitate one-time scheduling or CHS in every cluster on the basis of the RE-TOPSIS rank index value. In every round of LEACH's setup state series; this procedure entirely eradicates the requirements of the CHS procedure. Here, they had considered diverse criteria like distances among adjacent nodes, remaining energy, accessibility of neighboring nodes, rates of energy consumption; distances among the CHs and sink in addition to distances among CHs to member nodes; and the dependability index for entirely devising the novel method.

In 2018, Akinbode A. Olawole et al [4], worked on a novel hard decision fusion rule that creates the CH non-cooperative sensing effect an essential state for cooperative decision making. Additionally, this paper proposes an evaluative numerical examination of 3 conventional CHS methods regarding their performance in CSS, in varying cluster's heterogeneity and detection thresholds. A robust and generalized CHS scheme that surmounts the restrictions of the conventional models was subsequently developed. The performance of the conventional CHS methods based upon the distribution of secondary users compared with the detection threshold and the primary user's location.

In 2018, Achyut Shankar et al [5], developed a hybrid GGWSO method to enhance the performance of a CHS in WSN. Hence, the lifetime of the networks was prolonged. The proposed algorithm overcomes the most important constraints related to delay, distance, security, and energy. This study compares the performance of the proposed GGWSO with numerous conventional methods such as fractional ABC, GSO, ABC, and GWO-based CHS.

In 2019, L. Song et al [6], worked on the difficulty of cooperative coalitions chosen for CMIMO method to expand the average battery capability between the complete network, and subsequently suggest to be relevant the QPSO to choose the optimum cooperative coalitions of every hop in the routing path. Experimental results revealed that the proposed QPSO-based co-operative coalition’s chosen method could choose the best cooperative sender and receiver devices in every hop dynamically. Additionally, it was superior to the virtual MIMO method with a fixed number of cooperative devices.

In 2019, Khalid A. Darabkh et al [7], presented a novel EA-DB-CRP for collecting data in WSN that essentially aspires in distributing the load between obtainable SNs that in order balances the energy utilization in the network and as a result prolongs the lifetime of the network. The role of CH was turned between all cluster individuals, in a round-robin fashion, which was sorted in a list in descending order on the basis of a tremendously effectual CH weight in each sub-layer. In addition, there were a less number of cluster members preserved to security the possibility of clusters being created and this was by presenting a cluster merge method. Finally, a successful relaying method was presented in that CH obtain attentive of that SN positioned in a layer ahead to the BS beside with their relay-node weights while every CH selects the relay node which had the maximum weight.

3. System Model for Cluster Head Selection in WSN

From any remote environment, WSN is used for collecting and sensing the information so that it minimizes the human risk for gathering the data. The WSN consists of a huge number of the SNs which are clustered into groups. Additionally, one of these nodes is selected as the cluster head for transmission. The CHS carries out the duty of routing the gathered data to the base station. In the sensing environment, assume there is n number of sensor nodes, which are uniformly distributed. The SNs have the unique ID and the base station is centered in the optimal location so that the base station has the ability to receive all the clustered data from the SNs. The base station is indicated as, S^n which performed by receiving the gathered information of the SNs from the CH. Hence, the data transfer is operated by exploiting the CH-based routing model in the WSNs. Consider the cluster head as, CH and the number of the CHs are indicated as, g and $\underset{l \in n}{S^H_{n,l}}$ indicated the set of the SNs in the cluster group, S^H.

During the data transmission from the SN to the cluster head and subsequently, to the base station, the WSNs face a huge summons. The important problem is concerning the data transmission among the SN by the minimum path. The significance of deciding the minimum routing path is to enhance the communication speed and minimize the energy utilized at the time of communication. Hence, the frantic issue is to place the optimal CH based upon the energy and the position. In the optimal cluster head selection, the distance measure on transferring the data packets is controlled to be minimum so that the transmission energy is minimized that is enabled using the optimal head. Hence, it needs to use the optimization for choosing the optimal head. Fig 1 shows the system model of the WSNs.

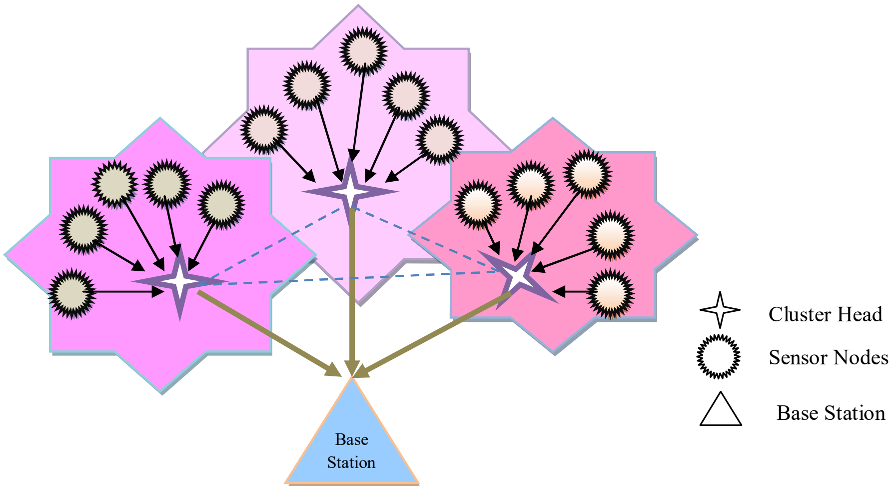

Fig. 1. *System model of WSN*

Each SN has the initial energy, which is indicated as, η_O and the SN available in the WSNs are battery-operated, which are non-rechargeable that is the one of the main cause behind fixing energy as an important constraint. The energy mislay happens while transmitting the message from any of the normal node to any of the cluster follows a multi-path fading and free space model based upon the distance among the sender and the receiver. In the nodes, the energy dissipation is because of the existence of the electronics and a power amplifier in the sender and the receiver in attendance in the nodes. The energy dissipated by any packet of size ps based upon the distance and the node nature. Nature is either head node or a normal node. The energy dissipation [8] occurs because of the transmission of energy using the normal node is stated as below:

$$\eta^{dis}\left(N_j^m\right) = \eta^E * ps + \eta^{ps} * ps * \left\|N_j^m - N_l^H\right\|^4 \text{ if } \left\|N_j^m - N_l^H\right\| \geq b_o \tag{1}$$

$$\eta^{dis}\left(N_j^m\right) = \eta^E * ps + \eta^{ps} * ps * \left\|N_j^m - N_l^H\right\|^4 \text{; if } \left\|N_j^m - N_l^H\right\| \geq b_o \tag{2}$$

where, $b_o = \sqrt{\frac{\eta^F}{\eta^{ps}}}$.

η^E indicates the electronic energy, η^{ps} indicates the energy associated with the power amplifier. In the free space, the energy is denoted as, η^F. The variable $\left\|N_j^m - N_l^H\right\|$ denotes the distance between the j^{th} normal node N_j^m and the l^{th} CH node N_l^H. The electronic energy is the summation of the transmitter energy $\left(\eta^T\right)$ and the data aggregation energy $\left(\eta^D\right)$ as stated in eq. (3).

$$\eta^E = \eta^T + \eta^D \tag{3}$$

When the data of size ps is transmitted to the cluster head, the energy dissipated is stated in eq. (4).

$$\eta^{dis}\left(N_l^H\right) = \eta^E * ps \tag{4}$$

Following a single transmission or receiving the data packets the nodes energy is updated shortly. In the nodes, energy updating is done using eq. (5) and (6).

$$\eta^{t+1}\left(N_j^m\right) = \eta^t\left(N_j^m\right) - \eta^{dis}\left(N_j^m\right) \tag{5}$$

$$\eta^{t+1}\left(N_j^H\right) = \eta^t\left(N_j^H\right) - \eta^{dis}\left(N_j^H\right) \tag{6}$$

In eq. (5), t indicates the current time of the measure. The energy updating follows until the node becomes a deceased node or while no energy subsist.

4. Proposed Methodology for Energy-Aware Routing in WSNs

Fig 2 shows the proposed algorithm for energy-aware routing. By exploiting the proposed MHSDE method, the optimal selection of CH is done. The presented method aspires at the chosen of the cluster head on the basis of the distance, delay, energy, and the traffic density. By MHSDE method the selection of CH is performed optimally which exploits the formulated objective model which must be reduced so that the distance for energy needed for transmitting the data packets, transmitting the data packets, delay transmission, and the traffic density is less, w the energy existing in the nodes should be increased. The objective model enables prolonged network lifetime and energy-aware routing. By the proposed MHSDE on the basis of the optimal cluster head is attained, the cluster head is altered for all the individual iteration. In the WSNs each SNs can hold the location as the CH.

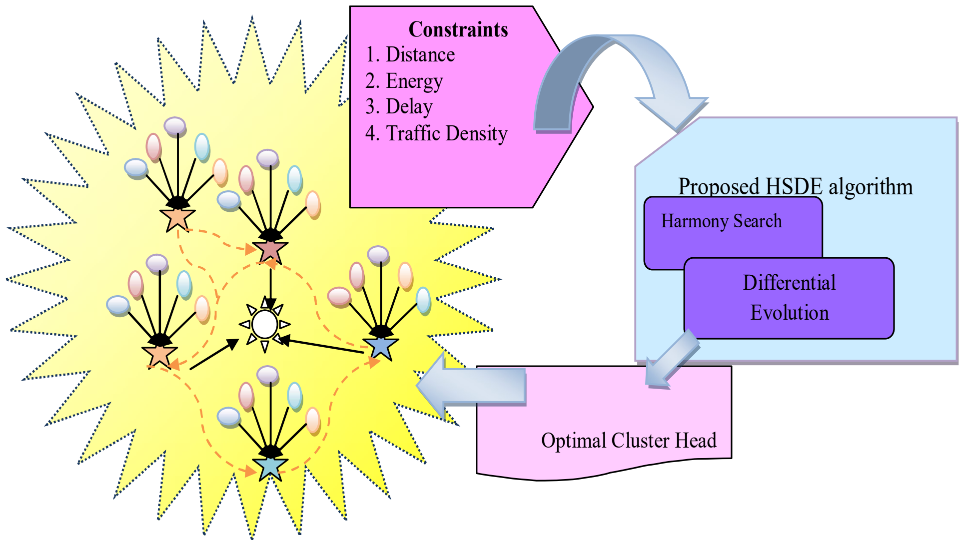

Fig. 2. *Schematic diagram of energy-aware routing by exploiting the HSDE algorithm*

For the energy-aware routing, the multi-constraints such as the energy, distance, traffic density, and the delay are utilized are in the WSNs. In this section, the significance of the energy-aware constraint in doing the routing in WSNs is elaborated.

a) Distance Measure

In WSNs the distance measure [8] explains the requirement of the distance parameter in the data transmission. When an SN is done as a CH, the distance between the cluster members is computed so that the distance must be less. The least distance is contemplated and the SN which is at the least distance from the CH is selected for the data transmission. In eq. (7), the formulation of distance measure is shown. In the distance formula, the numerator term represents the summation of the distance travelled by the data packet from the base station and the data packet from CH to the base station and to the cluster node. The value of the distance must lie among zero and one so that normalization is done. The denominator $\sum_{j=1}^{n}\sum_{l=1}^{n}\left\| N_j^m - N_l^H \right\|$ implicate the normalizing the distance values.

While the distance among the normal nodes to the CH is greater subsequent, the distance parameter obtains a higher value.

$$F_i^d = \frac{\sum_{j=1}^{n}\sum_{\substack{l=1 \\ l\in k}}^{h}\left\| N_j^m - N_l^H \right\| + \left\| N_l^H - S^n \right\|}{\sum_{j=1}^{n}\sum_{l=1}^{n}\left\| N_j^m - N_l^H \right\|} \tag{7}$$

In eq. (7), n indicates the total number of the nodes, and g indicates the total number of the CH. The normal node is indicated as, N^m, the CH is indicated as, CH, and the base station is indicated as S^n. N_l^H indicate the l^{th} CH.

b) Energy Measure:

In the network, the parameter of the energy must be high for the node that portrays the node energy is adequate to pursue the transmission of data. In the WSNs yet the energy for the transmission of data must be less. By subtracting the cumulative energies from 1 as stated in eq. (9) the maximization problem is changed into the minimization problem. The energy parameter [8] is an important parameter and the computation of the energy remaining in the node is on the basis of the cumulative energy of a cluster and the summation of the energies for all the clusters. The energy model is stated as below:

$$F_i^{\eta} = \frac{\sum_{l=1}^{h} N_c^{\eta}(l)}{h \times \underset{l=1}{\overset{h}{Max}}\left[\eta\left(N_l^m\right)\right] \times \underset{l=1}{\overset{h}{Max}}\left[\eta\left(N_l^H\right)\right]} \tag{8}$$

$$N_b^{\eta}(l) = \sum_{\substack{j=1 \\ j\in l}}^{n} \left[1 - \eta\left(N_j^m\right) * \eta\left(N_l^H\right)\right]; (1 \le l \le h) \tag{9}$$

The cluster energy that remnants minimum will choose as the better Cluster Head. The term $\sum_{l=1}^{h} N_c^{\eta}(l)$ indicates the cumulative energy of the complete CH and the term $h \times \underset{l=1}{\overset{h}{Max}}\left[\eta\left(N_l^n\right)\right] \times \underset{l=1}{\overset{h}{Max}}\left[\eta\left(N_l^H\right)\right]$ indicates the product of the total number of the CH and the maximum value of the energy of the CH and the other SN used in the transmission. The utmost value of the denominator term is one.

c) Delay Measure:

In [8], the delay has to be reduced in the network for the optimal CH and it is directly proportional to the number of members in the cluster. The delay rises with the number of the cluster members which assures that the cluster members gathered in the optimal cluster must be in less. Conversely, the number of cluster member determines the transmission delay. Hence, the cluster with the less number of the cluster members starts sending the data packets.

$$F_i^{\Delta} = \frac{\underset{l=1}{\overset{h}{Max}}\left(S_{n,l}^H\right)}{n} \tag{10}$$

In the network $S_{n,l}^H$ indicates the 1^{th} CH and the values of the delay deviate among zero and one.

d) Traffic Density Measure:

For the effectual network, the traffic density [9] must be less and the traffic density based upon the packet drop, buffer utilization, and channel load of the network and the computation of the traffic density based upon the average of these 3 parameters.

$$F_i^t = \frac{1}{3}\left[BU + PS + CL\right] \tag{11}$$

In eq. (11), BU indicate the buffer utilization, CL indicate the channel load and PS indicate the packet drop. The buffer utilization based upon the buffer size and buffer space that is stated in the eq. (12).

$$BU = \frac{B_{space}}{B_{size}} \tag{12}$$

$$PS = \frac{D_p}{PS_x} \tag{13}$$

In eq. (13), B_{space} states the buffer space, D_p states the number of packets dropped, B_{size} states the buffer size, and PS_x indicates the number of packets transmitted. The packet drop based upon the total number of the packets, which are transmitted and the total number of packets, which are dropped at the packet transmission of the data and it is stated in the eq. (13). Eq. (14) illustrates the channel load.

$$CL = \frac{C_{busy}}{TR} \tag{14}$$

In eq. (14), C_{busy} denotes the channels in the busy state and TR denotes the total number of the rounds stated in the experimentation time. Eq. (14) represents the formula of channel load which is based upon the state of the channels and the number of rounds stated in the experimentation time.

5. Optimized CHS in WSN using Multi-Objective HSDE

5.1 Conventional Harmony Search Method

In [10], Harmony Search is an evolutionary method that imitates musician's behaviors like memory-based play random play, and pitch altered play to obtain an ideal state of harmony. In the harmony search method, a new harmony is produced by three main operations, such as memory consideration, random selection, and pitch adjustment. The primary Harmony Memory (HM) comprises of an HMS (Harmony Memory Size) number of arbitrarily produced solutions for the optimization issue which are in consideration. Every module of harmony in HM is initialized with a uniformly distributed random number among the lower and upper bounds of the issue. The elements of a new harmony are arbitrarily produced from the searching space as stated below:

$$y_{m,n} = l_n + rn(\ ) \cdot (v_n - l_n) \tag{15}$$

In eq. (15) $y_{m,n}$ states the n^{th} element of the harmony y_m, and the harmony memory $HM = \{y_1, y_2, \ldots y_N\}$; v_n denotes the upper bounds l_n and the lower bounds of the m^{th} searching dimension; $rn(\ )$ produces a real arbitrary number uniformly distributed in [0, 1].

For the harmony search method in the memory consideration operation for every generation, the elements of a new harmony are arbitrarily selected from the harmony memory and that are stated as below.

$$u_{m,n} = \begin{cases} y_{rn,n} & rn(\ ) < HMCR \\ l_n + rn(\ ) \cdot (v_n \cdot l_n) & \text{else} \end{cases} \tag{16}$$

In eq. (16) $y_{rn,n}$ indicates the n^{th} element of the arbitrarily chosen harmony y_{rn}. Subsequently, the elements attained in the memory consideration operation are enhanced to their neighbors with the Pitch Adjusting Rate (PAR) as stated in eq. (17).

$$u_{m,n} = \begin{cases} u_{mn} + rn(\ ) \cdot r_n & rn(\ ) < PAR \\ u_{mn} & \text{else} \end{cases} \tag{17}$$

In eq. (17), r_n is indicates the random distance bandwidth for the n^{th} element.

When a novel harmony is produced, it will be evaluated with the poor harmony in the harmony memory. The conqueror will be retained in the memory.

5.2 Conventional Differential Evolution

In [11], DE is considered as the swarm evolutionary techniques at first presented for unconstrained function optimization issues. It noticed the solution of an optimization issue by memorizing the optimal trial for each individual and sharing the information of the population. Until now, numerous variants of the traditional DE was developed, it has been extensively exploited. Here, three main operations such as mutation, selection, and crossover are utilized.

Especially, the initialized population of DE is created using eq. (18).

$$y_{m,n} = l_n + rn(\ ) \cdot (v_n - l_n) \tag{18}$$

In eq. (18), $y_{m,n}$ represents the n^{th} dimensionality of the m^{th} individual of the population, l_n and v_n indicates the minimum and maximum value of it, correspondingly and $rn(\ )$ creates an arbitrary value distributed uniformly in [0, 1].

Eq. (19) denotes the performance of the mutation operators, r_1, r_2 and r_3 indicates 3 numbers that recognize 3 different individuals arbitrarily chosen from the mutation factor F and current population is a scaled coefficient among 0 and 1.

$$t_m^h = Y_{r1}^h + F \cdot \left[Y_{r2}^h - Y_{r3}^h \right] \tag{19}$$

Eq. (20) denotes the performance of the crossover operation, here CR indicates a real parameter among zero and one which controls the rate of crossover for the trial individual and the old individual. Subsequent to the operation crossover, eq. (20) is used to perform a greedy selection.

$$u_{m,n} = \begin{cases} t_{m,n} & rn() < CR \\ u_{m,n} & \text{else} \end{cases} \tag{20}$$

$$y_{m,n}^{h+1} = \begin{cases} u_{m,n}^h & f\left[u_{m,n}^h\right] < f\left[y_{m,n}^h\right] \\ y_{m,n}^h & \text{else} \end{cases} \tag{21}$$

It is obviously observed from Eq. (21) that the greedy selection assures that the subsequent population would not be worse than the present one. During the aforesaid operations, the population will move towards the global best of the issue besides the evolution procedure.

5.3 Proposed Hybrid Harmony Search Algorithm with Differential Evolution

The values of the crossover probability factor CR and scaling factor F and possess a direct effect on population diversity. The experimentation states that the lesser crossover probability factor and higher scaling factor it will be obliged to global searching and to attain better population diversity.

Nevertheless, they minimize the convergence speed of the method when improving the global searching capability. As a substitute, the individual difference of population will minimize with the maximizing crossover probability factor and minimizing the scaling factor. It leads to appear premature convergence and enhances the local searching capability.

The suitable parameters would directly manipulate the results of the method. Test results have exhibited that the method will attain superior results while CR and F are altering in a linear way. The eq. (22) and (23) indicates the dynamic CR and F are set up in a linear relation.

$$F_t = F_{max} - (F_{max} - F_{max}).t / T_{max} \tag{22}$$

$$CR_t = CR_{max} - (CR_{max} - CR_{max}).t / T_{max} \tag{23}$$

In eq.(22), T_{max} indicates the maximum number of iterations and t indicates the current iteration.

An enhanced mutation operation is combined into the HSDE to accelerate the convergence speed. Three individuals arbitrarily chosen are sorted using their fitness values in a specified order in the enhanced mutation operation. The sorted series from better to worst is Y^h_{rb}, Y^h_{rn} and Y^h_{rw}. Hence, the mutation operation changed as eq. (24). For the enhanced mutation operation, the method attains the superior individual Y^h_{rb} as the base vector and searches for the best solution to a superior differential vector $Y^h_{rn} - Y^h_{rw}$ that can enormously minimize the searching sightlessness. As the individuals used in the mutation operation are chosen arbitrarily, the biased arbitrary search would not minimize the global search capability of the proposed method.

$$t^h_m = Y^h_{rb} + F \cdot \left[Y^h_{rn} - Y^h_{rw}\right] \tag{24}$$

Subsequent to the conventional operations of mutation, crossover, and selection, a novel extra opposition with an arbitrarily created individual is developed into the proposed algorithm in order to efficiently swoop from the local optimum and improve the capability of global search. Eq. (25) is used to indicate the competition.

$$y^{h+1}_{m,n} = \begin{cases} y^h_{m,n} & f\left[u^h_{m,n}\right] > f\left[y^h_{m,n}\right] \\ u^h_{m,n} & \text{else} \end{cases} \tag{25}$$

In eq. (25) $u^h_{m,n} = l_m + rn(\;) \cdot (v_n - l_n)$.

Although DE executes entirely in resolving incessant optimization issues, it is not an effectual method for varied integer optimization issues. As the state of a unit is 0–1 integer variable, a few alterations have to be performed for the unit obligation while exploiting DE. Moreover, the fundamental difference operation is altered as eq. (26), here, $\otimes$ indicates “AND” $\oplus$ indicates “OR”.

$$t^h_m = Y^h_{r1} \oplus \left(Y^h_{r2} \otimes Y^h_{r3}\right) \tag{26}$$

6. Results and Discussions

6.1 Simulation Procedure

The simulation of the proposed algorithm of CHS in the WSNs was performed in the system. The proposed algorithm of energy-aware routing protocol, that optimizes the CH and minimizes the energy utilized, was utilized. The algorithm used for the evaluation such as ABC, LEACH, and PSO in order to prove the efficiency of the presented method. Moreover, the evaluation was performed by evaluating the metrics, like normalized network energy, number of alive nodes, and the network throughput.

6.2 Performance Analysis

In this section, the comparative analysis of the routing protocols is examined. Here, 50 nodes are used for the evaluation, and the analysis is performed for 500, 1000, 1500 and 2000 rounds.

Fig 3 exhibits the performance analysis of the proposed and conventional models with respect to the number of alive nodes. For 2000 rounds, the proposed algorithm is 15% better than ABC, 13% better than LEACH, 21% better than the PSO algorithm. Fig 4 shows the performance analysis of the proposed and conventional models with respect to the network energy. For 1500 rounds, the proposed algorithm is 22% better than ABC, 25% better than LEACH, 29% better than the PSO algorithm. Fig 5 shows the performance analysis of the proposed and conventional models with respect to the network throughput. The proposed algorithm is 12% better than ABC, 18% better than LEACH, 17% better than the PSO algorithm for 1000 rounds.

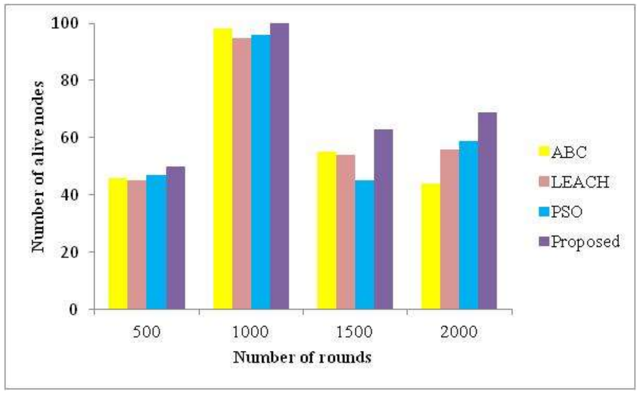

Fig. 3. *Performance analysis of the proposed algorithm regarding the number of alive nodes*

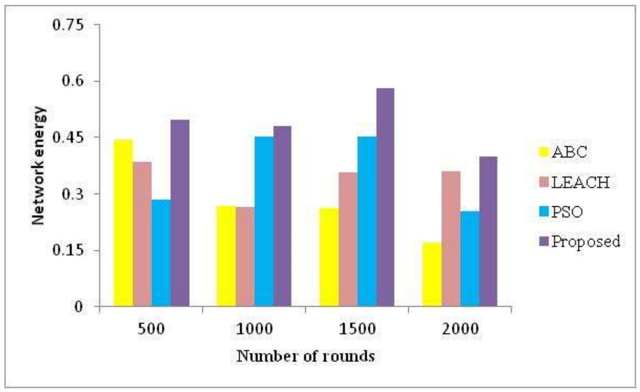

Fig. 4. *Performance analysis of the proposed algorithm regarding the Network energy*

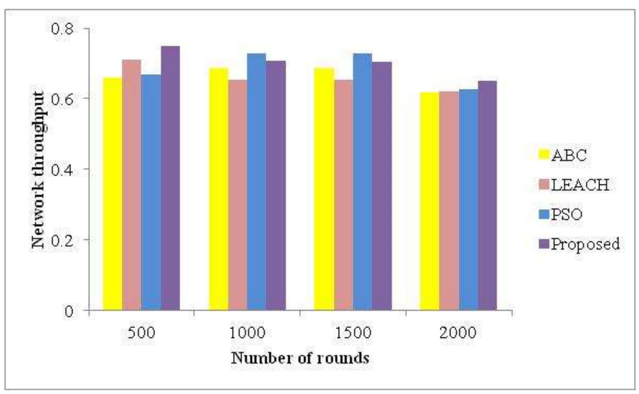

Fig. 5. *Performance analysis of the proposed algorithm regarding the network throughput*

7. Conclusion

In this paper, the energy-aware routing by exploiting the proposed MHSDE method was proposed which surmounts the drawbacks of the conventional algorithms. The proposed algorithm focused on four most important constraints, like delay, energy, distance and traffic density in order to calculate the optimal CH to carry out the communication in the WSNs which was the major model of the proposed MHSDE method. By exploiting the proposed MHSDE algorithm the energy-aware routing presents the integrated effect of both the HS and the DE. The experimentation was done utilizing the two WSN architectures with 50 nodes that show the results of the proposed MHSDE, which was better than the conventional methods. Moreover, it was revealed that even if the energy minimizes with the rising number of rounds, the residual energy in the nodes was maximum relating to other methods and the throughput stayed superior correspondingly.

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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