

Energy-aware Cluster Head Selection in WSN using HPSOCS Algorithm

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Abstract: Wireless Sensor Network (WSN) is represented as cheap as well as power-efficient sensor nodes that efficiently transfer data to the Base Station (BS). However, the energy, distance, with time delay is considered as the important challenges in WSN. Here, the power source of the Sensor Node (SN) is considered as a non-rechargeable battery. Moreover, the higher the distance among the nodes, the greater the energy utilization can occur. The Cluster Head (CH) method is exploited for the efficient transmission of data with minimum energy. Moreover, the time delay is directly proportional to the distance among the nodes and the BS. In such a way, the CH is chosen, which is spatially nearer to the BS and the SN. Hence, the time delay can be considerably minimized. Therefore, the transmission speed of the data packets is maximized. In this paper, Particle Swarm Optimization (PSO) with Crow Search Algorithm (CSA) is presented for choosing the CH. While comparing with other conventional methods such as PSO and CSA, the performance of the network is maximized.

Keywords: WSN; Cluster Head; Base Station; Sensor nodes; Energy

Nomenclature

Abbreviations	Descriptions
WSN	Wireless Sensor Network
FCM	Fuzzy C-Means
SN	Sensor Nodes
HRFCHE	Hyper-Exponential Reliability Factor-based CHS
GA	Genetic Algorithm
PSNs	Public Safety Networks
FBECs	Fuzzy Based Balanced Cost CH Selection
CHES-PC	Cluster-Head Selection Scheme with Power Control
PSO	Particle Swarm Optimization
BS	Base Station
CSA	Crow Search Algorithm
GSO	Glowworm Swarm Optimization
FFOA	Fruitfly Optimization algorithm
CHS	Cluster Head Selection
CSS	Cooperative Spectrum Sensing
IEECHS	Improved Energy Efficient CHS

1. Introduction

Nowadays, the WSN is considered as one of the optimistic modal [1] [2]. Generally, the WSN inspects the environment by means of identifying the changes that happened in monitoring areas [9]. Some changes occurred in the environment are sound, vibration, temperature, pressure, humidity, intensity, and motion. In several monitoring system fields, the applications of WSN are extensively exploited [10]. Here, the fields such as military solicitations, habitat, and health monitoring system, bio-medical applications, smart home monitoring system as well as inventory management system. Moreover, the energy effectuality plays an important role in WSN and it is responsible for improving the network lifetime. This objective can be attained by a suitable CH selection so that the communication link is accepted among the BS and the WSN [11] [12].

Generally, an SN needs to check the accessible area. Subsequently, it needs to transfer the outcomes to the sink with respect to a message. Transmitting data into the sink needs effectual management, whereas thousands of nodes are distributed in the applications area like forest monitoring. In order to gather the data from the network area, a variety of approaches are presented [25]. However, the maximum consumption of the energy network is considered as the performance evaluation criteria for these approaches. It happens due to the unavailability of recharge nodes battery in many applications of sensor networks. Hence, in WSN the energy saving is considered as significant methods. Various researches have concentrated on clustering of the network to minimize the energy consumption through clustering scheme. In addition, some researchers are focused on routing method for energy saving of WSN [13] [14] [24].

Since clustering is exploited for connecting a network in a hierarchical way. An energy effectual, as well as vigorous manner of transmission, is attained by the clustering method in that nodes are classified as well as arranged into small clusters. Every cluster has a CH that needs to forward aggregated data from member nodes to the BS directly or via a progression of CHs [15]. Moreover, clustering offers huge benefits against flat architecture namely network scalability, minimizing inter-node communication, bandwidth management and permitting nodes to sleep for a period of time following in energy savings. Selection of CH is a significant task of any cluster-based method, which can directly affect the performance of the network. On the basis of a single principle, selection of CH selection e.g. remaining energy can tend to worst performance due to the chosen CH might not be a better option. Addition to remaining energy, other parameters namely distance from other nodes and cluster centroid, etc. needs to contemplate for best CHS [16] [17].

The main aim of this paper is to propose HPSOCS-based CHS in WSN, by considering three parameters namely energy, distance, as well as delay. The hybridization of PSO and CSA methods can improve the performance of CHS against other well-known optimization methods. The rest of the paper is organized as follows: Section 2 describes the related works and section 3 describes the network model and problem formulation for CHS in WSN. Section 4 states the optimized cluster head selection approach and section 5 describes the results and discussions. Section 6 defines the conclusion of the paper.

2.Related Works

In 2017, Qingjian Ni et al. [1], adopted a solution based on the clustering preprocessing and PSO method for CHS in hierarchical topology control. On the basis of the geographical location, to start the clustering for sensor nodes the fuzzy clustering approach was exploited. Moreover, the number of initial clusters and the SNs depends on a cluster with a solution probability. Then, the fitness factors were computed, which consist of the distance and energy consumption factors of WSN. At last, on the basis of the enhanced PSO, the CH nodes in hierarchical topology were determined.

In 2018, Akinbode A. Olawole et al. [2] discussed on a cluster-based CSS in cognitive radio networks, which offers the minimized sensing error, delay reports and enhanced efficiency of energy in a network. Though, to attain the benefits appropriately determine the CH selection and implement a suitable fusion rule. Here, a novel hard decision fusion rule was implemented that creates the CH as a non-cooperative sensing outcome, which was an obligatory circumstance for cooperative decision making. Additionally, under the cluster's heterogeneity and varying detection thresholds, this paper presented a relative numerical investigation for three conventional CHS methods in terms of their performance in CSS. However, the performance of the conventional CHS methods was based on the secondary user's distribution comparative to the main user's location, as well as the threshold detection.

In 2018, Kale Navnath Dattatraya and K. Raghava Rao [3] worked on a well-known clustering approach to create the transmission of data in an effectual manner. Generally, the clustering method splits the SNs into several clusters. Each cluster in a sensor network holds different CHS that transmit the information to other SNs in the cluster. In that condition, the clustering technique plays an important role to select the best CH with several limitations such as minimum energy utilization, delay and so forth. Here, a novel CHS method was developed to increase network lifetime and energy efficiency. Additionally, a new Fitness based hybridization of GSO and FFOA to select the optimal CH in WSN.

In 2018, S. Anthony Jesudurai and A. Senthilkumar [4] presented an IEECHS-WSN approach, it was exploited to transmit the obtained information by employing an efficient energy routing protocol. In CHS approach, dual CH was chosen in a separated cluster and its work in a variety of functions. Hence, the network lifetime was extended and the energy utilization was minimized for IoT applications. As well as, the proposed method was stated on the clustering of two CHs in the approach of data fusion for data entropy. For fusion and classification, the information entropy was exploited, the outcome of fusion and classification were precise as well as competent for data transmission.

In 2017, Bilal Muhammad Khana et al. [5] presented a Fuzzy-TOPSIS method on the basis of the multi-criterion decision making to decide CH competently and efficiently to increase the WSN lifetime. Here, various principles were considered namely number of neighbor nodes, remaining energy, rate of node energy utilization, and the average distance among neighboring nodes. To minimize energy consumption, a threshold-based inter-cluster, as well as the intra-cluster multi-hop communication scheme, was exploited. The effect of node density was also examined as well as various types of mobility schemes were utilized to examine the impact on the lifetime of WSN. In WSN, to increase the load distribution, predictable mobility with the octagonal route was presented.

In 2018, A. Amuthan and A. Arulmurugan [6] worked on the effectiveness of the CHS procedure, which was in charge for solving the problems of network management, which aspires to enhance the prolonged existence of the sensor network. Many of the energy inspired CHS techniques to contemplate all the contributing SNs as real. Likewise, the trust-based CHS approaches presume all cooperating SNs to be energy-related. These assumptions exploited in the energy or trustworthy-on the basis of CHS that was not sensible in nature and the present energy accessibility of SNs may not assist in solving the best CH of the network. Here, a trust assessment and energy integrated prediction method was presented that was known as HRFCHS by Semi-Markov method for enhancing the lifetime of the network.

In 2018, Pawan Singh Mehra et al. [7], presented an FBECS method that consists the distance from the BS, remaining energy, and the node density in its neighborhood as input to Fuzzy Inference System. Here, for each SNs, the eligibility index was computed for the chosen of the CH role. By selecting optimal aspirant for the position of the controller of clusters, the protocol assures the load balancing. Finally, the probability was allocated for each sensor nodes.

In 2018, Abdul Rahim Ansari and Sunghyun Cho [8] worked on a clustering approach, which was implemented for PSNs. Hence, they presented a clustering-based CHEAD-PC for PSNs this strategy exploited FCM as a clustering tool. The outcomes reveal that the proposed method considerably minimizes the power utilization of the network.

3. Network Model and Problem Formulation for CHS in WSN

3.1 WSN

In WSN, all the sensors are motionless and each sensor possesses uniform abilities. Generally, a cluster node can act as dual modes (i.e.,) CH as well as an active sensor. The WSN deals with data sensing, topology features, radio communication, energy utilization, and sensor position. In an application area, the sensors can be placed arbitrarily or manually. The BS can directly connect with all sensors in all WSN. Fig. 1 demonstrates the systematic representation of the CH with the communication of the sensor to the centralized BS.

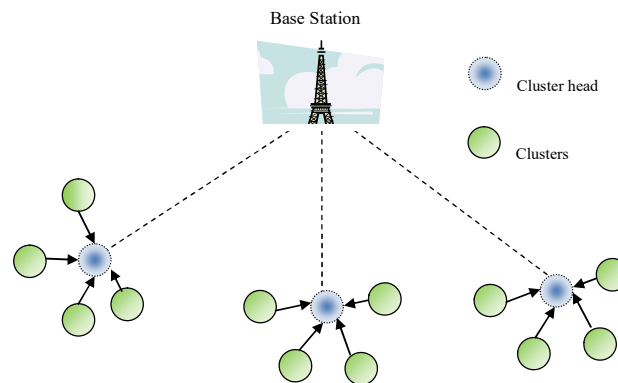


Fig. 1. Systematic diagram of WSN

On the basis of some conditions, the analysis of cluster or clustering is referred as the function of collecting a set of sensor nodes, where the sensor in the similar group is more same to each other than to those in other groups. Additionally, in WSN the clustering is considered as the technique for extending the network lifetime. Also, it entails the nodes to be assembled to form the clusters and selecting CH (N_c) for the whole number of clusters. The SNs that have a small distance to the nearby CH (N_c) in WSN. One of the important tasks of the sensor is to collect data from the targeted area and proceed it to the CH. Subsequent to the CH proceeded the gathered information to the base station.

3.2 Distance Measure

Initially, all the chosen CH transmits the notice message within the network, notifying that they proceed as the CH. Now, every single SN of the network calculates the distance among every CH. The nodes connect the CH with a small distance and provide the nearby CH with a message. The sensor node will connect directly with BS while the CH distance from the node overshoots its distance to the station. In the remaining circumstances, it connects with a cluster, in conformity with their close distance; hence it creates the clusters. Subsequently, the nodes are reclustered in the context to space with the chosen CH with the assist of a $DM(m * n)$, which represents the distance matrix indicated in eq. (1).

$$DM(m * n) = \begin{bmatrix} d_{N_{c1},x_1} & d_{N_{c1},x_2} & \dots & d_{N_{c1},x_n} \\ d_{N_{c2},x_1} & d_{N_{c2},x_2} & \dots & d_{N_{c2},x_n} \\ \vdots & \vdots & \ddots & \vdots \\ d_{N_{cm},x_1} & d_{N_{cm},x_2} & \dots & d_{N_{cm},x_n} \end{bmatrix} \quad (1)$$

The d_{N_c} , which is used in eq (1) indicates the Euclidean distance among the CH (N_c) as well as a node on the basis of its location information and x_1, x_2, \dots, x_n represents the SNs. While y and z indicates the position of the two SNs p and q , and the euclidean distance can be calculated as eq. (2). As this eq. (2), every element in the matrix represents the distance, which subsists among the p^{th} CH and the q^{th} node. Utilizing the related node the column which possesses the minimum value in the matrix points to the cluster number needs to experience the link.

$$d_{p,q} = \sqrt{(p_y - q_y)^2 + (p_z - q_z)^2} \quad (2)$$

Let us consider an example; here d_{N_{c2},x_1} resides the first column with a small value. In such a condition, the CH gets connected with the node x_1 and the second cluster with N_{c2} .

To every single member, N_c allocates a time slot, afterward the receipt of messages from the whole number of CH and at once subsequent to the clusters are arranged in all cluster nodes. The task of each CH is to attain information from the total number of nodes that it holds. Instantly, a data frame is obtained from every member while the N_c transfers the data to the BS. N_c Remnants in a vigorous condition, throughout the time the SNs function in sleep mode from one instantaneous to the other. Until all the SNs become dead, the reclustering performance and transmission of data follow for a number of cycles.

With respect to the distance from the receiver to the transmitter, both the free space and multipath fading channel is exploited. Subsequently, a free space method is utilized at once a particular threshold value presumes a greater value than the distance. In the other condition, the multipath fading model is used while the threshold value is low. The threshold distance is represented in eq. (3).

$$d_0 = \sqrt{\frac{E_{fs}}{E_{pw}}} \quad (3)$$

Where, E_{fs} represents the energy need when utilizing free space model and E_{mp} represents the power amplifier energy.

3.3 Energy Measure

In WSN, one of the major problems is the battery utilization. Once the battery of the sensor nodes is exhausted, it cannot be recharged and there will be a lack of power supply. The SN minimizes its energy and transmits the data to Base Station. The energy utilization method states the method of the network minimizes energy in different operation namely reception, transmission, aggregation, and sensing. The total energy needs to transfer the messages is represented in eq. (4).

$$E_{TX}(N : d) = \begin{cases} E_{el} * N + E_{fs} * N * d^2, & \text{if } d < d_0 \\ E_{el} * N + E_{pw} * N * d^2, & \text{if } d \geq d_0 \end{cases} \quad (4)$$

Where, $E_{TX}(N : d)$ represents the utilization of total energy which transmits packets in N bits at distance d and E_e represents the energy need in per bit transmits circuitry. The total energy needed in obtaining packets in N is stated in eq. (5). The energy needed for amplification is represented in eq. (6). The total energy cost, which is related to a network is stated in eq. (7).

$$E_{RX}(N : d) = E_e N \quad (5)$$

$$E_{am} = E_{fs} d^2 \quad (6)$$

$$E_{total} = E_{TX} + E_{RX} + E_1 + E_S \quad (7)$$

The value of eq. (7) should be reduced. where, E_1 represents the energy cost during idle state, E_S represents the energy cost while sensor is indicated in eq. (8) and E_{el} represents the electronic energy.

$$E_{el} = E_{TX} + E_{ae} \quad (8)$$

In eq. (8), E_{ae} represents the data arrogation energy.

3.4 Multi-Objective Function

In order to transmit the information, the delay must be low and the cluster member distance from the CH must be preserved minimum based on the principle of WSN. However, the energy-related to every cluster should presume a maximum value. The objective function of the CHS must reduce the subsequent objective function as stated in eq. (9). The value of β must be in the range $0 < \beta < 1$ in eq. (9), and by exploiting eq. (10) and (11), the functions f_b and f_a can be solved. In eq. (10), σ_1 , σ_2 and σ_3 represent the energy, distance, as well as the delay that are the constant parameters. However, it must maintain the state $\sigma_1 + \sigma_2 + \sigma_3 = 1$.

$$F_n = \beta f_b + (1 - \beta) f_a \quad (9)$$

$$f_a = \sigma_1 * f_i^{dis} + \sigma_2 * f_i^{ene} + \sigma_3 * f_i^{del} \quad (10)$$

$$f_b = \frac{1}{n} \sum_{x=1}^n \|N^x - B_s\| \quad (11)$$

Eq. (12) indicates the fitness function for the distance.

$$f_i^{dis} = \frac{f_{(a)}^{dis}}{f_{(b)}^{dis}} \quad (12)$$

$$f_{(a)}^{dis} = \sum_{x=1}^{N_c} \left[\|C_x - B_s\| + \sum_{y=1}^{N_x} \|C_x - X_x\| \right] \quad (13)$$

$$f_{(b)}^{dis} = \sum_{x=1}^{N_c} \sum_{y=1}^{N_y} \|C_x - X_y\| \quad (14)$$

As in eq. (12), the value of $f_{(a)}^{dis}$ must adds the distance that is associated with the packets, which are carried from normal node to the CH and to the BS at an afterward instantaneous. The certain value must be minimum within the range 0 to 1. While the normal node distance from the CH is maximum, the value of f_i^{dis} becomes high. In eq. (13) and (14), C_x indicates the x^{th} CH, X_x indicates to the node presented in x^{th} CH and N_y states the number of nodes, which are not presented in the x^{th} CH.

Eq. (15) represents the fitness function for energy while the whole CH cumulative $f_{(a)}^{ene}$ and $f_{(b)}^{ene}$ presumes energy to be of utmost value and the CH utmost count, subsequent the value of f_i^{ene} becomes higher than one

$$f_i^{ene} = \frac{f_{(a)}^{ene}}{f_{(b)}^{ene}} \quad (15)$$

The fitness function of delay is directly dependent on the number of members, which occupied among a cluster. Hence, the CH possesses a small number of members to reduce the delay. In eq. (16), the fitness function for the delay is indicated. Here, the numerator represents the maximum amount of CH and the denominator holds all the nodes in the network. The value of f_i^{del} must be minimum for the fitter CHS and within the range of 0 and 1.

$$f_i^{del} = \frac{\max \left(\|C_x - X_x\| \right)_{x=1}^{N_c}}{N_c} \quad (16)$$

4. Optimized Cluster Head Selection Approach

4.1 Conventional Optimization Algorithms

a) Conventional PSO algorithm:

Kennedy and Eberhart [18] introduced the PSO method [22] that is a stochastic swarm-based intelligence approach, which is an extensively well-known algorithm due to the competent searching scheme. As same as the GA [21], the PSO technique is enthused by the combined behavior of bird flocks. The locations and velocities of P particles in the d -dimensional space present arbitrarily initialized solutions in the PSO technique. Eq. (16) represents the solution of a particle m in the iteration i . The present solution of every particle is subsequent to updated in terms of the local and global optima that are calculated exploiting eq. (17) and (18).

$$Y_m^i = \{y_{m,1}^i, y_{m,2}^i, \dots, y_{m,d}^i\} \quad m = 1, 2, \dots, P \quad (16)$$

$$u_{m,n}^{i+1} = \sigma u_{m,n}^i + c_1 r_1 (g_{m,n}^i - y_{m,n}^i) + c_2 r_2 (g_{best}^i - y_{m,n}^i) \quad (17)$$

$$y_{m,n}^{i+1} = y_{m,n}^i + u_{m,n}^{i+1} \quad (18)$$

where $y_{m,n}^i$ indicates the location and $u_{m,n}^i$ indicates the velocity of the particle m in dimension n and σ is an inertia weight, which effects the convergence speed. The local optimum g_m^i and global optimum g_{best}^i indicate the current optimal position as well as the optimal position in the swarm between all particles over the time period i . The constants c_1 indicate the cognitive and c_2 indicate the social parameters, and r_1 and r_2 are arbitrary variables in the interval $[0, 1]$.

b) Conventional Crow Search Algorithm

Generally, Crows are considered as one of the cleverest birds. In fact, their behavior represents a high level of cleverness only to some extent below that of humans. For instance, crows show self-awareness in mirror experiments and display tool-making abilities. Actually, each crow has its own hiding place for saving food and obtains protections to guard this protect from other crows, it potentially goes behind the first crow to take the saved food. The CSA [19] is a newly developed stochastic swarm-based intelligence method, which is designed to determine function optimization problems.

In the CSA algorithm, the individual comprehensives are defined as crows. Here, two important parameters for crows have presented namely the flight length f_l and the awareness probability AWP . The value of f_l corresponds to a local search or global search and the AWP controls the crow intensity or diversity. By the CSA, these crows are arbitrarily created at particular positions. The fitness values are calculated and utilizing eq. (19), the position of each crow in the present population is updated. The position of crows m in an iteration i that offers a possible solution for P crows is represented in eq. (19). Where, Y_m^i indicates the possible solution for crow m in dimension n , and d indicates the dimension number for the solution space.

$$Y_m^i = \{y_{m,1}^i, y_{m,2}^i, \dots, y_{m,d}^i\} \quad m = 1, 2, \dots, P \quad (19)$$

For each crow, the present solution is updated in accordance with one of two conditions. In the first condition, it is presumed that crow c does not identify that crow m is in the chase. In the second condition, it is supposed that crow c identifies that crow m is in the chase. Utilizing eq. (20), the updated position for each crow is calculated.

$$y_{m,n}^i = \begin{cases} y_{m,n}^i + \text{rand}_m \bullet f_l \bullet (l_{c,n}^i - y_{m,n}^i) & \text{if } \text{rand}_v \geq AWP \\ \text{random position} & \text{otherwise} \end{cases} \quad (20)$$

where $y_{m,n}^i$ indicates the location of a crow m in the dimension n of iteration i , and $l_{c,n}^i$ indicates the hiding place position of the crow c in the dimension n of iteration i . Moreover, f_l states the flight length of the crow m in iteration i , AWP states the awareness probability of crow c in iteration i , and rand_i and rand_v are arbitrary variables in the interval $[0, 1]$.

4.2 Proposed Algorithm

Section this paper, the HPSOCS algorithm is presented this the hybridization of which PSO [23] and CSA algorithms. Moreover, the proposed method includes concurrently performing the PSO and CSA algorithms and guiding the solution to the global optimum utilizing the HPSOCS method. From the PSO and CSA methods, some individuals are chosen exploiting chosen methods and are exchanged

subsequent the processing of a specific number of iterations. At last, a local search operator is exploited to enhance the solution quality.

Individual velocity:

For each particle, the solution space is searched and its solution it's updated exploiting eq. (17) during consecutive iterations. A time-varying maximum velocity U_{\max} is used to control the oscillations in the PSO method. Eq. (21) and (22) defines the velocity thresholds.

$$U_{\max} = \left(1 - \left(\frac{i}{i_{\max}} \right)^h \right) \times U_{\max 0} \quad (21)$$

$$U_{\max 0} = \alpha \times (y_{\max} - y_{\min}) \quad (22)$$

In eq. (21) the exponent h represents the positive constant, α controls the bounds at each velocity of the search space, y_{\min} and y_{\max} is the position thresholds, i is the iteration and i_{\max} represents the maximum iteration.

Hybrid operator:

At specific operation represent the hybrid operator. Here, few individuals are chosen from the CSA and PSO approaches and interchanged exploiting the chosen methods. Here, random selection is used along with the probabilities depending on the fitness values in eq. (23), where ft_i represents the fitness value for the individual t in the population.

$$\text{Pr ob}_t = \frac{ft_t}{\sum_{t=1}^P ft_t} \quad (23)$$

Local Search operator:

Here, the local search operator utilized is in this same to the Differential Evolution crossover operator [20]. Representing crow c as the optimal of an individual crow, $y_{c,n}^{i+1}$, and particle n considered as the optimal one of PSO particles, the local search operator presents recombination among the original optimal solution for the crow (particle) in each dimension as eq. (24). Here, $y_{m,n}$ indicates the position of the t^{th} crow in dimension n .

$$y_{m,n}^{i+1} = \begin{cases} (y_{m,n}^i) & \text{if } f(y_{m,n}^i) < (y_{m,n}^{i+1}) \\ y_{m,n}^{i+1} & \text{otherwise} \end{cases} \quad (24)$$

Algorithm: Pseudocode of the proposed method

For each particle and search agent

Initialize each search agent

End

Do

For each particle and search agent

Compute the fitness value using eq. (23)

If the fitness value is superior to the optimal fitness value

Set the current value as the new g_{best}

End

Best solution is found

Select the particle and search agent with an optimal fitness value

Calculate velocity using eq. (21) and (22)

End

5. Results and Discussions

5.1 Experimental Procedure

The proposed HPSOCS-based CHS in WSN experiments in MATLAB R2015a. In WSN, the total number of nodes is represented as N_N that is allocated in the area $100m \times 100m$, whereas at the center the base station is placed. The corresponding experimentation is performed from 0 to 2000 rounds. By exploiting the energy, distance, and delay the objective function of WSN is computed. At the time of the simulation, the initial energy E_i is set as 0.5 and the energy of power amplifier E_{pw} is set as $10pJ/bit/m^2$. In addition, the transmitter energy E_{TX} is assigned as $50nJ/bit/m^2$ and the data aggregation energy E_{ae} is fixed as $5nJ/bit/signal$. On the basis of assigned values, the experimentation and the consequent performance analysis are performed by comparing the proposed HPSOCS approach with conventional approaches such as PSO and CSA.

5.2 Performance Analysis

In this section, the performance analysis of the proposed HPSOCS technique with conventional approaches like PSO and CS approach is shown and it is analyzed till the 2000 rounds. Moreover, it explains the different number of CH produced with decreased or increased distance.

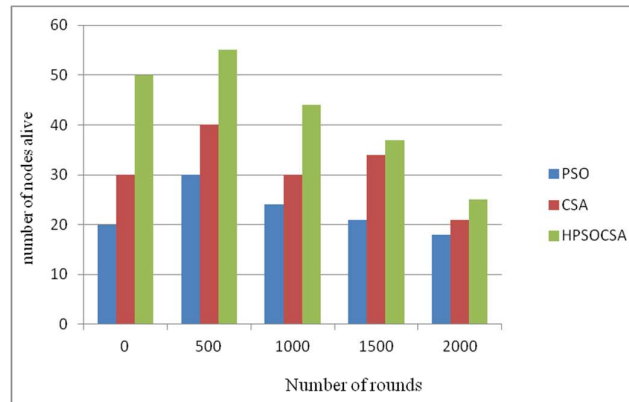


Fig. 2. Performance analysis of alive nodes regarding the number of rounds

The analysis of alive nodes regarding the number of rounds is shown in Fig 2. Here, it demonstrates the alive node analysis with the periodic rounds, until the completion of 2000 rounds. The performance of proposed and conventional techniques is analyzed for each round. In all the techniques, 50 nodes remain alive until 500 rounds. Subsequently, the number of alive nodes minimizes when the round maximizes. Finally, at round 2000, nearly 28 nodes stay alive for the proposed HPSOCS approach that portrays better performance than the conventional. Fig. 3 demonstrates the number of alive nodes regarding the distance. At every single round with particular distance, the proposed HPSOCS method shows that the distance is minimum with increased alive nodes while comparing with the existing approaches.

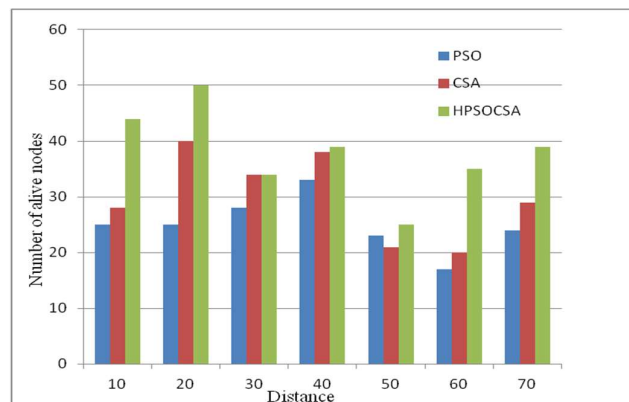


Fig. 3. Performance analysis of alive nodes with respect to distance

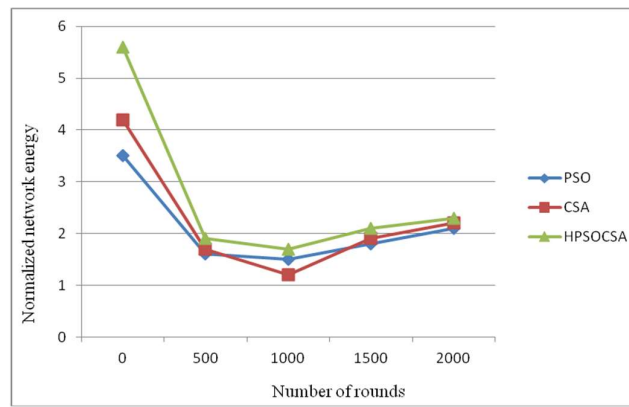


Fig. 4. Performance analysis of normalized network energy regarding the number of rounds

The performance analysis of normalized network energy for each round is demonstrated in Fig 4. Here, the normalized energy for 100 nodes is analyzed. From the pictorial representation, the energy until 2000 rounds the performance of the proposed approach found to present the maximum energy, while making comparison over all the other conventional approaches for experimentation rounds, which range among 0 and 2000. Fig. 5 portrays the normalized network energy with respect to the distance. The performance of the proposed HPSOCS method exhibits that it attains maximum energy at a higher or lower distance among each node against the traditional approaches.

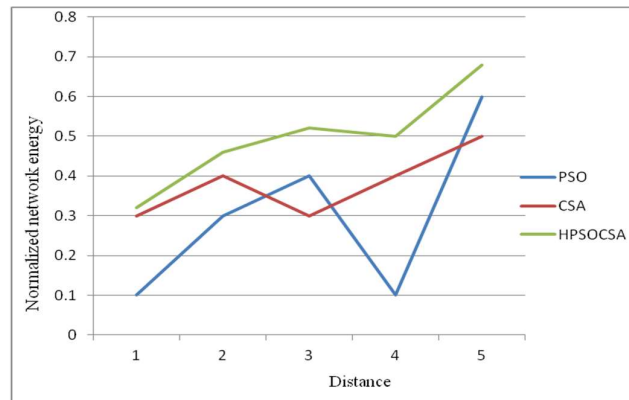


Fig. 5. Performance analysis of Normalized network energy with respect to Distance

6. Conclusion

In this paper, the implementation of CHS in WSN exploiting HPSOCS was presented, which was the hybridization of PSO and Crow search algorithm. Generally, the major issue of WSN is related to the transmission of data with high energy conservation and minimum delay. These issues were concentrated on the present work whereas its main contribution was to encourage an effectual CHS by taking into consideration the energy, distance, as well as sensor nodes delay among the network. Furthermore, the HPSOCS based CHS performance was compared with existing methods such as PSO and CS methods. This comparison has equipped by the accurate analysis and it was shown the capability of HPSOCS to maintain multi-objectives. Hence, the network energy by HPSOCS protocol has conserved, the distance among the nodes was minimum and a huge amount of alive nodes has subsisted. As a whole, the proposed HPSOCS algorithm was superior to the traditional CHS methods. The attained outcomes were promising and perform better than the traditional algorithms, and hence the issue of CHS is further resolved by initiating additional progressions in the meta-heuristic rules.

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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