Hybrid Crow Search and Particle Swarm Algorithmic optimization based CH Selection method to extend Wireless Sensor Network operation

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Abstract – In ad hoc wireless sensor networks, the mobile nodes are deployed to gather data from source and transferring them to base station for reactive decision making. This process of data forwarding attributed by the sensor nodes incurs huge loss of energy which has the possibility of minimizing the network lifetime. In this context, cluster-based topology is determined to be optimal for reducing energy loss of nodes in WSNs. The selection of CH using hybrid metaheuristic algorithms is identified to be significant to mitigate the quick exhaustion of energy in entire network. This paper explores the concept of hybrid Crow Search and Particle Swarm Optimization Algorithm-based CH Selection (HCSPSO-CHS) mechanism is proposed with the merits of Flower Pollination Algorithm (FPA) and integrated Crow Search Algorithm (CSA) for efficient CH selection. It further adopted an improvedPSO for achieving sink node mobility to improve delivery of packets to sink nodes. This HCSPSO-CHS approach assessed the influential factors like residual energy, inter and intra-cluster distances, network proximity and network grade during efficient CH selection. It facilitated better search process and converged towards the best global solution, such that frequent CH selection is avoided to maximum level. The outcomes of the suggested simulation HCSPSO-CHS confirm better performance depending on the maximum number of active nodes by 23.18%, prevent death of sensor nodes by 23.41% with augmented network lifetime of 33.58% independent of the number of nodes and rounds of data transmission.

Keywords – Wireless Ad Hoc Sensor Networks, Enhanced Particle Swarm Optimization Algorithm (EPSOA), Flower Pollination Algorithm (FPA), Crow Search Algorithm (CSA), Network Lifetime, Sink Node Mobility.

I. INTRODUCTION

In WSNs, every sensor node comprises of components such as sensor, power supply, transceiver, memory and a processing unit.The main objective of the sensing node aims in monitoring and capturing the environmental parameters such as sound, temperature, pressure, etc., as required by the application [1]. The processing unit can perform computation over sensed data and generates appropriate actuation commands and signals [2]. The transceiver is accountable for sending as well as receiving radio signals to and from a node within shared communication range. The nodes are efficient incontrolling error, flow, congestion and routing based on network size [3]. There is also a possibility that the nodes may drain their energy when they are in an idle state. WSNs are deployed for collecting data with respect to one or more phenomena in varied environments, such as likelihood of disasters, seismic zones, civilian monitoring, and tracking applications [4]. In addition, the quality of human life can be significantly enhanced with WSN application domains like smart learning, agriculture, health, smart home, security and surveillance, etc [5]. to achieve better QoS in these applications, the sensor nodes require more capability in terms of processing power, energy, data aggregation, and communication.

These WSNs can be deployed in one of the following scenarios, based on the application-specific requirements that includes, i) Static sinks and static nodes, ii) Static sink and mobile nodes, iii) Mobile sink and static nodes and iv) Mobile sink and mobile nodes [6]. Static sink with static nodes deployment scenario is more suitable for application areas such as surveillance, industrial monitoring applications, etc, involving no mobility of sensor nodes [7]. In a static deployment scenario, the distances between various sensor nodes are unchanging. In this setup, the sensors adjacent to the sink can use direct communication for energy conservation [8]. Further, nodes located away from the sink derive the advantages of other collaborating sensor nodes for sending packets to sink. The nodes close to sink node spend more energy due to data forwarding, even though they do not communicate their data [9]. WSNs are extensively used for real-time applications that help in tracking or observing events. WSNs are posed with various challenges that include limited energy, computational overhead, constrained bandwidth while establishing connectivity among the collaborating sensor nodes [10]. The chief objective of WSNs is to extract environmental parameters, perform data communication, and forward aggregated data to BS, with an extended network lifetime. Several energy-conserving mechanisms have been proposed to avoid the deprivation of connectivity in the network. The routing protocols intended for sensor networks are impacted by varied factors that need to be addressed to attain effective communication. In specific, routing plays a substantial role in WSNs and poses numerous unsolved challenges. The routing protocols are proposed to solve the issues in WSNs. Clustering mechanism is appropriate foraddressing a variety of routing challenges in WSNs [11].

The complete network is partitioned into self-organized clusters during clustering. After clustering, a potential sensor node which satisfies the objective function is preferred as Cluster Head (CH). These CHs are essential for gathering the sensed facts from member nodes and forwarding them to sink [12]. Moreover, hierarchical sensor network implementation relies on the process of clustering which is completely targeted on specifying potential roles to the sensor nodes at different network architectural levels. This clustering process of WSNs concentrates on energy optimization that enhances network lifespanand energy efficiency [13]. Furthermore, Cluster formation is the procedure of organizing sensor nodes into groupsand CH selection in every group of WSNs represents a problem of optimization. This CH selection problem belongs to the NP-hard complexity class problem since it targets the objectives of improving throughput, extended network lifetime and balanced energy consumption during each round of implementation process [14]. The predominant swarm intelligent meta-heuristic optimization algorithms contributed for CH selection are Artificial Bee Colony (ABC),Ant Colony Optimization (ACO),Cuckoo Search (CS), particle swarm optimization (PSO)and its variants, Differential Evolution (DE) etc., [15]. At this juncture, it is identified that the exploration capability of CSA (CSA-based CH selection) integrated with exploitation potential of enhanced PSO algorithm (in finding ideal locations for placing a sink) can help in improved energy consumption with prolonged lifetime.

This article contains, Hybrid Crow Search and Particle Swarm Optimization Algorithm-based CH Selection (HCSPSO-CHS) mechanism is proposed with merits of enhanced chaotic crow search and improved PSO to augment network lifespan and energy stability in WSNs. This HCSPSO-CHS approach assessed the influential factors such as residual energy, network lifetime, travelled distance, delay in data collection and packet loss into account to achieve efficient CH selection. It integrated PSO and enhanced version of CSA together to facilitate better search process and converge towards the best global solution, such that frequent CH selection is avoided to the maximized level. It also adopted opposition-based learning strategy in the exploitation stage of hybrid algorithm to prevent impotent sensor nodes using existing chosen as CH. The simulation results of proposed HCSPSO-CHS confirm maximized quantityof active links and reducedamountconsisting of non-functioning nodes with augmented network lifetime independent ofquantity of sensor nodes and rounds of data transmission.

The remaining sections are structured as follows. **Section 2** gives review of comprehensive swarm-intelligent CH selection models contributed to literature considering their advantages and disadvantages. **Section 3** gives a detailed suggested perspective CSA-based CH selection and EPSO-based sink node mobility, energy and objective model considered during its implementation in the network. **Section 4** gives the outcomes of simulation along with analysis related to performance of proposed HCSPSO-CHS scheme and benchmarked CH selection models evaluated using Packet Delivery Rate (PDR), network lifetime, packet delay and energy consumptions with a variable quantity of terminals. **Section 5** gives the conclusion along including significant achievements and potential for additional enhancement.

II. RELATED WORK

The [16] contributed a Bacterial Foraging and Fruitfly Optimization Algorithm (BFFOA) for constructing energy potent clusters with optimized CH selection for extending the network lifespan and energy. This BFFOA adopted energetic elements, both within and between clusters, and number of neighbouring nodes considered in the assessment of nodes that measure achieved using fitness function. In [17] proposed a energy efficient clustering protocol using Genetic Spider Monkey Optimization algorithm (GSMOA) for improving the nodes' lifespan and energy stability. This GSMOA protocol implemented CH selection using three steps that includes, i) set-up phase and ii) steady phase. It facilitated energy potent clusters for enabling data packets to reach sink from source in setup phase. On the other hand, the issues of load balancing was handled according to inclusion of dual-hop broadcasting between clusters and within clusters data broadcast strategies into account during steady state. It was identified to minimize the control overhead by relying on the method of energy-based opportunistic broadcasting depending on the arise of requirements in the network. It was identified to outsmart the baseline schemes based on end to-end delay, energy consumption, network lifetime, control overhead and throughput independent of systematic increase in number of nodes.

The [18] have proposed a hybrid Whale and GWO (WGWO)-Power Harvesting-based grouping WSNs (EH-WSNs). Two meta-heuristic schemes namely, Whale as well as GW is proposed to increase the efficiency of clustering scheme. Exploitation as well as exploration competencies of the propounded approach are more than the conventional existing meta-heuristic schemes. The proposed scheme deals with formation of clusters and dynamic CH selection.Alghamdi (2020) have focussed on designing a clustering model with ideal CH selection by considering distance, energy, delay, and security. For choosing ideal CHs, a hybrid scheme that includes both dragon fly and firefly algorithms is proposed. The performance is analysed by comparing with other conservative models based on amount of alive nodes, energy consumed, delay as well as risk probability. In [19] have propounded a hybrid WOA-Moth Flame Optimization (MFO) which is considered to choose ideal CH that in turn enhances above-mentioned parameters. The performance is assessed with prevailing schemes based on energy-based factors. The findings make it evident that the propounded scheme outdoes the present methods.

Further [20] have dealt with several goals including delay reduction as well as energy sustainability by implementing a clustering scheme based on inter-distance amid the CH as well as nodes. Optimization variables including distance, delay as well as energy are considered for efficient CH selection. To design an improved model, an advanced scheme for CH selection using updated Rider Optimization Algorithm (ROA) is propounded. Solutions are organized into different sets depending on fitness. The first set is modified based on mean value of bypass as well as follower riders, whereas the second set is modified by considering the mean value of attacker as well as overtaker riders called Fitness Averaged-ROA (FA-ROA). Performance is analysed in terms of amount of alive nodes as well as normalized energy. The authors [21] have presented a cluster-dependent routing by choosing ideal CH. GW updated WOA is proposed. A multi-objective function is defined based on constraints including distance, security, delay as well as energy. Performance of proposed security-based clustering is assessed and confirmed in contrast to traditional works based on number of alive nodes, throughput including normalized network energy.

The [22] have proposed a Hybrid Shuffled Frog Leaping and improved Biogeography-based Optimization Algorithm (HSFLBOA) for optimum selection of CHs and determining the issues which are common in CH selection. The proposed scheme involves an objective function that depends on factors including energy of nodes, transmission delay, traffic density and distance between nodes. It is obvious that aforementioned suggested scheme provides enhanced efficiency as well as system strength as opposed to the standard meta-heuristic ideal CH mechanisms. The [23] have used MOA with energy-effective routing protocol for dealing with CH selection. When the role of CH is assigned to different nodes depending on optimization, the amount of energy consumed redundantly helps in solving the energy hole problem. Performance of the proposed Mobile Sensor node Energy Coherent MOA (MECMOA) is assessed based on distance, remaining energy and energy consumption rate. In addition, performance of propounded mechanism is associated with LEACH, LEACH_PSO and Stable Energy Efficient Clustering Protocol (SEECP) regarding the duration of a network's existence, number of active and inactive nodes along with PDR. It is obvious from the results that MECMOA enhances network lifespan, exhaustion ratio of nodes and energy consumption rate for each node.

In [24] have proposed an enhanced form of PSO for ideal selection of CHs. The efficacy of the approach is investigated and in comparison to prominent optimization mechanisms. The propounded mechanism offers enhanced outcomes depending on remaining energy, amount of live and dead nodes along with convergence rate. Efficient choice of CHs improves the network lifespan. The [25] has proposed a scheme to optimally select the CH using hybridized model called Lion Updated Dragonfly Algorithm (LU-DA) that is a combination of DA and LA. Furthermore, ideal choice of CH is performed based on energy, distance, delay, security as well as trust. Optimal selection of CH guarantees improved network lifespan. The proposed scheme offers improved performance based on and number of alive nodes. In addition, The [26] have proposed WOA-P which decreases the power consumption level and the duration of system operation are extended. It is found that the proposed scheme offers improved outcomeswhen compared to standard optimization schemes like DE, GA, PSO and GWO. The scheme improves efficiency by dropping the amount of energy consumed. As CHs have added accountability, there is increased energy drain causing irregular network degradation. LEACH balances this by probabilistically assigning the CH role amid nodes involving energy above a set threshold.

Extract of the Literature

Review over the existing hybrid CH selection protocols aided in finding the ensuinglimitsas stated below.

- Most of the channel preference methods need to assign weights to all the complete set of deployed node before the commencement of the clustering process.
- They failed in achieving better performance in the construction of global cluster with maximized time of execution.
- They always require knowledge based and lacks self-organization characteristics.
- They suffer from problem of slow convergence during refined search stage and have the likelihood of getting trapped into local search area.
- They need to maximize the iteration to get the optimal value

The aforementioned limits of present hybrid CH selection protocols motivated the design of the proposed Crow Search and Particle Swarm Optimization Algorithm-based CH Selection (HCSPSO-CHS) mechanism-based Clustering mechanism for improving andensuring the reliability of power and the longevity of the system.

III. HYBRID CROW SEARCH AND PARTICLE OPTIMIZATION ALGORITHM-BASED CH SELECTION (HCSPSO-CHS) MECHANISM

In this section, the comprehensive view of network, energy, distance and objective models considered during implementation of proposed HCSPSO-CHS mechanism is detailed.

Network Model

The WSN includes ‘n’sensor nodes along with a BS. This network model of the WSN holds the ensuing properties.

- The nodes are arbitrarily distributed in the 2-D plane of the environment under observation which comprises of distinctive latitude as well as longitude position points.
- The Nodes exhibit a high level of energy efficiency, once they are positionedwithin the surroundings, they cannot be recharged.
- The sensors are reliable and hold distinctive processing as well as transmission abilities. They consume same amount of energy for transmitting and processing data bits.
- After deployment of sensor nodes in the environment under observation, they remain static with respect to the BS. The sensors have similar chances to behave as a normal node or a CH.
- The nodes should sense data about the environment that is to be sent to the CH. The quantity of nodes should be more than amount of CHs.
- The BS’s location is variable based on the performance analysis in sensing area.
- The path of wireless transmission amid the nodes and the CHs is found within the region of transmission.
- Lastly, the nodes can gain diverse communication power hierarchies based on distance of data transmission.

An Analysis of Energy Consumption

By using Energy utilisation model [27], total quantity of energy consumed (E) depending on quantity of energies dissipated by the Transmitter (E_T) and receiver (E_R) are computed.

$$E_{Tot}(n,\varphi) = E_T(n,\varphi) + E_R(n) \tag{1}$$

Where,
$E_{Tot}(n,\varphi)$ - Total amount of energy consumed
$E_T(n,\varphi)$ - Energy used to activate radio amplifier as well as gadgets for power

Transceiver energy consumption for sending ‘n’ bits of data is represented as:

$$E_T(n,\varphi) = \begin{cases} n \times E_{Bit} + n \times AE_{FS} \times \varphi^2, \text{if } \varphi < \delta \\ n \times E_{Bit} + n \times AE_{MP} \times \varphi^4, \text{if } \varphi \geq \delta \end{cases} \tag{2}$$

Where
E_{Bit} - Energy spent per bit to implement the transmitter
AE_{FS} - Amplification Energy of Free Space model
AE_{MP}- Amplification Energy of Multi-Path model
δ - Threshold of communicating distance, $\delta = \sqrt{\frac{AE_{FS}}{AE_{MP}}}$
φ - Distance factor to calculate the power usage of the transmission based on quantity of sending of data

If transmission of data is within ‘δ’, then transmittance energy equals ‘φ^2’; Else, ‘φ^4’. The distance and workload are taken as substantial factors to enhance network lifespan.

Further, the amount of energy used by receiver for obtaining n-bit of data (E_R^n)is represented as:

$$E_R^n = n \times E_{Bit} \tag{3}$$

The total network lifespan (L_N) is calculated depending on Residual Energy (E_{Res}) and total energy of node (E_{Tot}) after transmission and reception, the data (n-bit) is represented as follows:

$$L_N(S_i, CH_j) = \frac{E_{Res}}{E^i_{Tot(n,\varphi)}} \tag{4}$$

Where,
$S_i \in SN$ - 'i' number of Sensor nodes
CH_j - 'j' number of CHs elected
$L_N(S_i, CH_j)$ - Network lifetime related to 'S_i' and 'CH_j' elected
E_{Res} - Residual energy of sensor node
E^i_{Tot} - Total energy consumed by nodes

In this context, the network lifespan during CH selection process is computed using First Node Dead (FND).

Distance Configuration

Usually, any communication between sensor nodes and CH, and CH and BS may demand some quantity of energy based on role or location of the node. Data transmission between sensors with increased distance consumes more power. Instead, the data transmission between nodes with minimized distance incurs less energy in the network. This distance from a node (i) to the BS is represented using Eq. (5).

$$\varphi_i = \sqrt{(X_{BS} - X_i)^2 - (Y_{BS} - Y_i)^2}, = \ 1,2, \dots, SN \tag{5}$$

Where,
φ_i - Distance of node (i) to BS
X_{BS}, Y_{BS} - X-Co-ordinate and Y-Co-ordinate of BS
X_i, Y_i - Location of 'i^{th}' node
SN- Amount of nodes positioned

The Euclidean distance amid sensor node and CH is shown below:

$$\varphi\left(SN_i, N_{CH_j}\right) = \sqrt{\left(X_j - X_i\right)^2 - \left(Y_j - Y_i\right)^2}, i = 1,2, \dots, SN, j = 1,2, \dots, N_{CH} \tag{6}$$

Where,
N_{CH} - Amount of CHs

The Objective Model

The fitness function for achieving CH selection in WSNs are residual energy, distance within and between clusters, network coverage and node degree. The definition of each of the fitness evaluation factors are presented below.

- Residual Energy (RE): It is the quantity of energy possessed by every node performing the activity of routing as specified in Eq. (1):

$$RE = \sum_{j=1}^{n} \frac{1}{En_{CH_j}} \tag{7}$$

- Distance within and between Clusters (D): The amount of energy consumed during transmission increases with distance. When BS is away from a node, more energy will be expended. The CH with shortest Euclidean distance from BS is preferred. Inter and intra cluster goals represented as 'ED_1' and 'ED_2' can be minimized using Eq (8) and (9).
-

$$ED_1 = \sum_{j=1}^{m} dist1(CH_k, BS) \tag{8}$$

$$ED_2 = \sum_{k=1}^{q} \sum_{j=1}^{cm_k} \frac{dist2(S_j, CH_k)}{cm_k} \tag{9}$$

where,
cm_k- Number of systems in the group
$dist2(S_j, CH_k)$ - The separation among 'S_j' and 'CH_k'

- Network coverage: It is defined the radius of communication covered by each sensor nodes as shown in Eq (10)

$$Net_{Cov} = rad(n_j) \tag{10}$$

Where,
$r(n_j)$ - Radius covered by node

The objective is provided based on Eq (11)

$$Net_{Cov} = \frac{1}{Nn_T} \sum_{j=1}^{n} Net_{Cov}\ (n_j) \tag{11}$$

- Node Degree: It representsquantity of nodes which are not CHs which go to particular portable node as shown in Eq (12).

$$n_{Deg} = \sum_{j=1}^{n} I_j \tag{12}$$

Consequently, Normalization (F(x)) is applied on each objective 'φ_1', 'φ_2', 'φ_3', 'φ_4', 'φ_5' as seen in Eq (13).

$$F(x) = \frac{f_i - f_{Min}}{f_{Max} - f_{Min}} \tag{13}$$

where,
f_i - Function value
f_{Min} and f_{Max} - Minimum and maximum fitness values

In this context, a potential trade-off needs to be preserved within objectives. Lastly, the objectives are transformed into a single function by adding the products. This multi-objective function that gives the fitness is formed in IDBBWOA as shown in Eq (14) and (15).

$$Fit = \varphi_1.RE + \varphi_2.D_1 + \varphi_3.D_2 + \varphi_4.Net_{Cov} + \varphi_5.n_{Deg} \tag{14}$$

Where,

$$\sum_{i=1}^{5} \varphi_i = 1 \text{ and } \varphi_i \in (0,1) \tag{15}$$

φ_i - Weighted parameter initialized randomly in the range [0, 1]

In this case, the value of the weighted parameters with respect to residual energy, distance within and between clusters, network coverage and node degree is set to φ_1= 0.4, φ_2= 0.3, φ_3= 0.2, φ_4= 0.05, φ_5= 0.05. respectively.
In specific, transmission distance is minimized as distance and RE are taken into consideration when selecting a node with increased RE [28]. Fitness functions are used for finding the best transmission path. Once a CH is chosen, clusters are formed based on distance as well as energy. In routing, the available routing schemes involve fitness functions and minimization procedures depending on distances to CH. In addition to distances, parameters like queue length as well as link quality are involved to lessen energy consumption and improve network lifespan.

Solution Representation
In this proposed scheme, classical CSA-based optimization scheme is used for selecting energy-aware ideal CHs in the network. The solution illustration for proposed scheme is formulated as represented in **Fig 1.** wherein (CH_1,CH_2, …,$CH_{N_{CH_j}}$) are the CHs.

CH_1	CH_2	… …	… …	… …	… …	$CH_{N_{CH_j}}$

Fig 1. Solution Representation used in FP-improved CSA Strategy

Primitives of Crow Search Algorithm (CSA)
This traditional CSA algorithm was proposed by Askarzadeh [27] depending on the inspiration derived from intelligent foraging characteristics of crows in hiding and retrieving food. The mathematical process involved in the optimization procedure of CSA is detailed below:

- Step 1: Initialise the following factors of CSA
  n - Size of populace
  Max_size - Maximum number of iterations
  SF - Step-size of Flight
  PP - Perception Probability
- Step 2: Initialize crows and memory matrix
  Generate crows (n) in the Search Space (SS) of D-dimension. Each crow $C_i = (C_i^1, C_i^2, \ldots, C_i^d)$ signifies a possible solution of the problem. As the preliminary populace lacks experience, the primary memory matrix is considered as the preliminary location
- Step 3: Assess the crow's quality based on fitness function
- Step 4: Produce a fresh position for every crow in SS with D-dimensions. Assume that every crow(i) arbitrarily follows another (j) to determine the location of the concealed food of 'j'. the location update of 'i' is split into ensuing 2 situations:
  - ✓ Case 1: 'j' does not know that 'i' follows it. The location update of 'i' is

$$X_i^{iter+1} = X_i^{iter} + r_i + SF_i^{iter} \times \left(m_i^{iter} - X_i^{iter}\right) \tag{16}$$

  - ✓ Case 2: 'j' knows that 'i' follows it. 'j' takes 'i' to an arbitrary location.

The place update of 'i' is

$$X_i^{iter+1} = \begin{cases} X_i^{iter} + r_i + SF_i^{iter} \times \left(m_i^{iter} - X_i^{iter}\right), & r_j \geq PP \\ \text{Random location}, & \text{Otherwise} \end{cases} \quad (17)$$

where,

r_i, r_j- Random numbers which follow uniform distribution of $[0, 1]$

PP - Perception probability

When 'PP' is lesser, the likelihood of happening of Case 1 is better. The algorithm inclines to explore locally. In Case 2, when 'PP' is more, the likelihood of determining is more, and algorithm inclines to search universally.

SF_i^{iter} - Length of Flight step of 'i'

When '$SF_i^{iter} < 1$', next location of 'i' is between 'X_i^{iter}' and 'm_i^{iter}'. When '$SF_i^{iter} > 1$', the next location of 'i' is beyond the line between 'X_i^{iter}' and 'm_i^{iter}'. Hence, 'SF' affects the algorithm's search capability. In case the value is huge, it inclines to search universally, leading to reduced convergence. For smaller values, there are high chances for falling into local optimum.

- Step 5: Check whether location of every crow is possible. If feasible, modify crow's location. Else, it is not modified.
- Step 6: Compute fitness of new location of every crow
- Step 7: Update crow's memory matrix

$$m_i^{iter} = \begin{cases} X_i^{iter+1}, & f\left(X_i^{iter+1}\right) \text{ is superior to } f\left(m_i^{iter}\right) \\ X_i^{iter}, & \text{Otherwise} \end{cases} \quad (18)$$

- Step 8: Repeat steps 4-7 till condition to terminate is met

Fundamentals of Flower Pollination Algorithm (FPA)

Flower Pollination (FP) algorithm is a meta-heuristic Swarm Intelligence (SI) optimization algorithm propounded by [28]. It mimics the methods of cross as well as self-pollination of flowering plants that agrees to global as well as local searches. As the algorithm is simple involving limited number of parameters with easy application, it has extensively fascinated the interest of several researchers.

To make the problem simple and enhance algorithm efficiency, it is assumed that the optimization problem has only one solution. It is considered that every flowering plant produces a flower which has a pollen gamete.

FPs are based on the ensuing rules:

- Cross-Pollination (CP) that is biological is global wherein carriers transmit pollen on Levy Flights (LFs)
- Self-pollination that is abiotic is considered as local pollination
- Probability of reproduction includes flower constancy comparative to the resemblance of 2 flowers
- Transition probability ($Tr_p \in [0, 1]$) is involved for controlling the shift from local to global pollination

A mathematical model is formed based on the above-mentioned rules.

In global pollination, pollen location update is given by,

$$X_i^{iter+1} = X_i^{iter} + L \times \left(X_i^{iter} - g_{Best}\right) \quad (19)$$

where,

X_i^{iter+1} - Solution of '$iter + 1$' generation

X_i^{iter} - Solution of 'iter' generation

g_{Best} - worldwide ideal outcome

L - Phase frequency following a Levy distribution

The value of 'L' is given by,

$$L \sim \frac{\gamma \Gamma(\gamma) \sin\left(\frac{\pi\gamma}{2}\right)}{\pi} \cdot \frac{1}{S^{1+\gamma}} \left(S \gg S_0 \gg 0\right) \quad (20)$$

where,

$\Gamma(\gamma)$ - Gamma function

The value of 'γ' is taken as 1.5.

The location update for partial pollination is given below:

$$X_i^{iter+1} = X_i^{iter} + \varepsilon \times \left(X_j^{iter} - X_k^{iter}\right) \tag{21}$$

where,
'X_j^{iter}' and 'X_k^{iter}' - Arbitrarily choose solutions varying from 'X_i^{iter}' in the populace
ε - Probability of reproduction, a random number in constant distribution of $[0,1]$

Transition amid global as well as local pollination is controlled by transition probability ($Tr_p \in [0,1]$). Several simulation investigations show that optimised performance of the algorithm is obtained when '$Tr_p = 0.8$'

Improved FPA-based CSA for CH Selection

To enhance the speed of convergence and accuracy, two approaches such as probability of self-adaptive perception and enhanced CP scheme of FP algorithm into the traditional CSA as specified in [25]. The detailed view of the proposed FPA-based CSA is mathematically represented as follows.

Probability of Self-Adaptive Perception

The PP has an increased influence on the performance of CSA. If 'PP' is more, the entities in the populace are persuaded to search globally but are not favourable to improve convergence accuracy. When 'PP' is smaller, the entities in the populace are motivated to carry out local search and drop into local optimum easily.

Nevertheless, if 'PP' is fixed, the global as well as local search capabilities can never be balanced. The inverse partial 'Γ' function is included to make 'PP' drop non-linearly to stabilise the global as well as local search competencies.

$$PP = \frac{1}{\left(\left(PP_1 \times \left(\frac{PP_2 - PP_1}{\gamma}\right) \times \Gamma\left(\gamma, \left(1 - \frac{Iter}{Iter_{Max}}\right)\right)\right) \times 100\right)} \tag{22}$$

where,
PP_2 - Upper limits of PP
PP_1 - Lower limits of PP
γ - Random variable
$Iter_{Max}$ - Maximum amount of iterations

The curve of non-linear 'PP' shows a decrease when $PP_1 = 0.05$, $PP_2 = 0.25$ and $\gamma = 0.01$. 'PP' is more during the commencement of iteration, making algorithm emphasis on global search. With each iteration, value of 'PP' declines progressively, making the algorithm to carry out local search, the populace focuses quickly, and convergence improves. Non-linear decreasing 'PP' can balance the global as well as local search, thus enhancing the algorithm's performance.

Enhanced Cross-Pollination (ECP)

From analysis of Equation (16), when a leader understands that he is followed, the location of the entity is arbitrarily produced. This approach to perform location update stops the system from dropping into local optimum to a particular degree. It diminishes the speed of convergence as well as the algorithm's accuracy. This problem is solved by presenting improved CP. Initially, it is expected that the crows get the universal optimal location depending on their knowledge as well as memory as thieves. Then, the concept of CP is used for efficiently guiding individuals to hover nearer to ideal entity to reach the ideal value. Nevertheless, CP has some limits. In later phases of iteration, it leads to decline of population diversity leading to dropping into local optimum and striving to jump out. By including the CP approach of Cauchy,

$$X_i^{iter+1} = g_{Best} + X_i^{iter} \times C(0,1) \tag{23}$$

Where,
$C(0,1)$ - Cauchy distribution

The crow's (search agent) location is updated as shown below.

$$X_i^{iter+1} = \begin{cases} X_i^{iter} + r_i + SF_i^{iter} \times \left(m_i^{iter} - X_i^{iter}\right), & r_j \geq PP \\ g_{Best} + X_i^{iter} \times C(0,1), & \text{otherwise} \end{cases} \tag{24}$$

In addition, **Algorithm 1** depicts the eagle view on the proposed FP-improved CSA algorithm-based CH selection as follows.

Algorithm 1. EFCSA

The FP-improved CSA algorithm for attaining CH selection in the network is presented below.
Input: Set of nodes with identified locations with search agents used for exploring as well as exploiting the network area (search space)
Output: Optimized number of CHs

Initialize the locations of search agents in the population randomly throughout the search space
Determine value of PP
for iter $= 1$ to $\mathrm{Iter}_{\mathrm{Max}}$
for i $= 1$ to n // Apply the process over the complete nodes of the network//
if ($r_j = \mathrm{PP}$)
Calculate $X_i^{iter+1} = X_i^{iter} + r_i + SF_i^{iter} \times \left(m_i^{iter} - X_i^{iter}\right)$
else
$X_i^{iter+1} = g_{Best} + X_i^{iter} \times C(0,1)$
end if
end for
Exploit and explore using the upper and lower thresholds of search space
Identify updating location of search agents (crows)
Modify the crow's (search agents') memory matrix
End for

Furthermore, the comprehensive clustering and subsequent CH selection processesof proposed HCSPSO-CHS mechanism is presented in **Fig 2.**

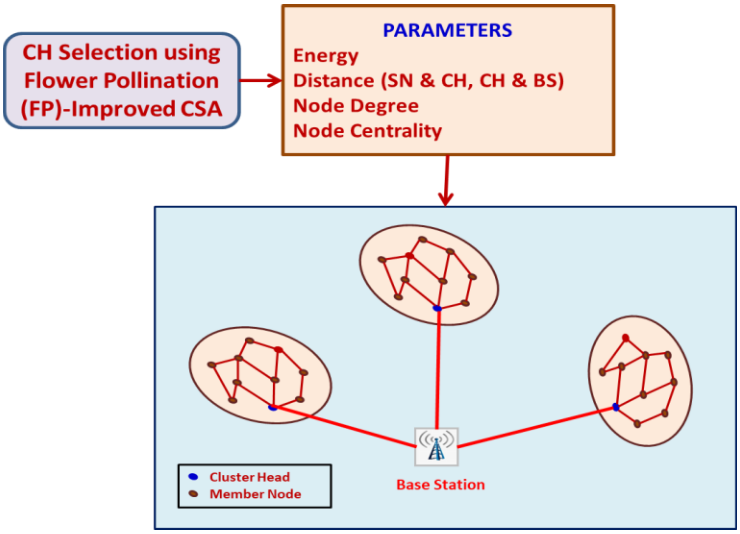

Fig 2. Process of Clustering and CH Selection Achieved using FP-improved CSA Algorithm

In the above-mentioned manner, the proposed FP-improved CSA algorithm calculated the fitness value and utilized the optimization algorithm for selecting sensor nodes with maximized fitness value in a more optimal manner to offer energy stability and network lifespan.

Enhanced PSO(EPSOA)-Based Sink Node Mobility

Within this particular segment, the detailed steps in procedure of EPSOA-regarding sink movement are presented. The proposed EPSOA-based sink mobility targets in maximizing the network lifetime by applying mobility to the sink as it has potential energy. In this EPSOA, the sink moves in a fixed trajectory. It waits at a trajectory location temporarily for a specific amount of time and, moves from region to another region depending on the requirement. In this case, the time of temporary stay in the location trajectory is the time gap determined between the reception of sensor data from the CHs, and its neighbouring nodes.

At the same time, the trajectory location represents the position of the network in which the sink temporarily waits for data collection, which is being the centre of each region. At the start, the temporary time of stay with respect to sink over each individual region is estimated. Then the temporary locations associated with the mobile sink are identified through the sojourn tour. However, this movement of sink node is highly influenced by the specified constraints and temporary time, energy possessed by the sink, the load to be balanced by the sink, thus this method of sink mobility represents a multi-objective optimization. This proposed EPSOA is utilized for determining the solutions of the optimization problem as it possesses maximized exploitation capability equal to the potentiality of its exploration.

Thus, EPSOA is utilized in the proposed mechanism for finding optimal points of positioning over the trajectory over which they can move for improved reception of data from selected CHs to sink. This EPSOA-based sink mobility is proposed depending on inspiration derived from improved PSO algorithm. When the functions involve high dimensions, the traditional PSO faces the premature issues along with reduced accuracy of optimization. The effect of joining PSO with Generalized Predictive Control (GPC) algorithm is also not good. Over the decade, the classical PSO is optimised using several techniques to overcome premature situation. One such strategy is the threshold judgment approachincluded to adjust PSO.

Primitives of PSOA

This PSOA includes restricted amount of particles (M) in the populace, each with attributes namely Position (P) as well as velocity (V). The particle moves toward the ideal location of the neighbouring area in every iteration [29]. The values of velocity as well as location are modified. The SS is of D-dimensions. The location of particle 'i' is represented as 'k_{id}'and velocity as 'v_{id}'.The maximum value of every particle is 'M_{id}' and that of the whole populace is called 'M_{gd}'. In every iteration, the particle fitness value determined during a current iteration is compared with the individual ideal fitness. One that is better is chosen for updating, and the ideal extreme value in the population is chosen for comparison and updating of the global optimum. The original PSO is represented as shown below:

$$v_{id}^{t+1} = \varphi v_{id}^{t} + c_1 rand(M_{id}^{t} - k_{id}^{t}) + c_2 rand\left(M_{gd}^{t} - k_{id}^{t}\right) \tag{25}$$

$$k_{id}^{t+1} = k_{id}^{t} + v_{id}^{t+1} \tag{26}$$

where,

φ - Inertia weight

$i = 1, 2, \ldots\ldots, m$

$rand$ - Random numbers between [0, 1]

c_1 and c_2 - Learning factors

The update of velocity is limited to $v_{id} \in [v_{id}^{min}, v_{id}^{max}]$

The position update is limited to $k_{id} \in [k_{id}^{min}, k_{id}^{max}]$

The values of 'c_1' and 'c_2' are taken as 2 is based on the experience.

Enhancement 1: Eliminate the Impact of Velocity

PSO mimics the foraging nature of birds. Each 'bird' continually updates the velocity as well and position, but the location update is only overlaid with velocity, which does not show the actual method of "foraging". Once analysis is done, it is seen that velocity need not be taken into account. In every particle optimization algorithm, the position term is made to move toward the ideal value substantially, and velocity signifies the 'moving direction' that brings the likelihood of going far away from the destination, called divergence. Velocity is eliminated and location is directly updated. This enhances the convergence velocity as well as accuracy to a particular amount. The Eq (25) and (26) are pre-processed by setting a value termed $a = c_1 r_1$, $b = c_2 r_2$and $d = \frac{aM_{id}^{t} + bM_{gd}^{t}}{a+b}$, such that the values of

$$v_{id}^{t+1} = \varphi v_{id}^{t} + (a+b)(d - k_{id}^{t}) \tag{27}$$

$$v_{id}^{t+1} = k_{id}^{t+1} + k_{id}^{t} \tag{28}$$

Again, from Equations (25) and (26), the values of k_{id}^{t+2} before sorting and after sorting is represented in Eq (29) and (30)

$$k_{id}^{t+2} = (1 - a - b)k_{id}^{t+1} + \varphi v_{id}^{t+1} + d(a+b) \tag{29}$$

$$k_{id}^{t+2} + (a + b - \varphi - 1)k_{id}^{t+1} + \varphi k_{id}^{t} - d(a+b) = 0 \tag{30}$$

From Eq (27), it is evident that velocity will have no impact on the algorithm, and the impact of velocity on algorithm's optimization is not seen following the elimination.

Enhancement 2: Weight Attenuation Approach joint with SR

Entropy signifies the level of chaos in the system; more the amount of chaos of the system, greater the entropy. The particle along with the PSO's SS can be considered as a system. PSO can be analysed from the variation of entropy. The entropy of the system (SR) changes with time in the process of optimization. When a particle drops into local optimum, SR takes a lesser value. Based on the concept of Minimum Entropy (ME), if the populace has no robust exterior interference, SR decreases and order increases. In case the particle desires to jump away from local optimization, system interference is imposed to raise the total entropy and improve the level of chaos.

In case of populace particle optimization, the co-efficient representing the inertia weight (φ) affects the particle hunt and accuracy of optimization. For a greater value of 'φ', the conforming capability of global search is strong. For a smaller value of 'φ', the conforming local search is precise. The weight enhancement is to make it reduce in medium amount during the iterative process. A global search is conducted in large-scale, and accuracy reduces in the future phase of iteration. Some implement weight decreasing mechanism of concave as well as convex functions. With increase in the amount of iterations, the speed of weight decrease decelerates.Nevertheless, this does not deal with the problem of PSO that falls into local optimization. Focussing on this problem along with SR, intermediate enhancement is added to weight attenuation process. The approach of increasing in the middle of iterations shows a trend of merging concave and convex functions.

A disturbance is included to improve the system entropy along with chaos. The function is to perform a global search at increased speed in the preliminary phase. At this time, some particles enter into local optimum, and the variation of location item is lesser. The amount of global search is increased to enable particles to jump from the state of local wandering and hunt for optimal value once more. Lastly, there is a reduction in weight and enhancement in the local search accuracy. The association amid weight and iteration times is shown below:

$$\varphi = \varphi_{max} + \left(\frac{1}{1+e^{-\frac{6T+12t}{T}}} - \frac{2t}{T}\right)(\varphi_{max} - \varphi_{min}) \tag{31}$$

$\varphi \in [\varphi_{max}, \varphi_{min}]$&t - Present iteration populace times

T - Maximum number of iterations in a population

e - constant

Based on the experience, when $\varphi = 0.8$, global optimum location can be reached at a faster rate. 'φ_{min}' is set to '0' and 'φ_{max}' is set to '0.8'.

Enhancement 3: Local Optimum Judgment Threshold

Typically, PSO falls into local optimization that makes the control effect inferior or incapable of meeting the demands. SR reduces and system becomes more orderly. To improve the global search capability which means increasing SR, the above sections dealt with reducing the local phenomenon during the iterative procedure, while the judgment threshold is detailed in this section.

During the iteration of the populace, as the number of times a particle's ideal value stops updating is more than the threshold, active location update scheme is executed to enable the particle to move to the historic location vector and in the reverse direction for re-optimization and raise the level of confusion as well as SR. This scheme focusses on determining the particle's moving phase and move away from the local optimum to enhance algorithm's performance.By considering the trajectory of particles, the particle's optimal value (M_{id}) after every location update is compared as well as updated. As the non-linear system is non-controllable, this mechanism is executed iteratively to preserve the global influence in the primary phase and local accuracy in the advanced phase. If 'M_{id}' for 4 successive times is similar to the former one, it is understood that the particle drops into local optimum. The particle location is updated again. The present motion location jumps away from local search by force based on the vector and inverse motion of historical motion locations to retain the liveliness of the particle. Local determination and location update scheme of the particle is detailed below.

$$Th_{id}^{t} = \begin{cases} 1, E_{id}^{t} = E_{id}^{t-1} \\ 0, E_{id}^{t} \neq E_{id}^{t-1} \end{cases} \tag{32}$$

where,

Th_{id}^{t} - Location judgment of the particle 'i' at time 't'

When the particle's optimal value is same as the one obtained previously, the value of judgment value is set to '1'; else, it is '0'. As the cumulative value of 4 successive values is same as the threshold, forced location update takes place.

$$\sum_{x=t-2}^{x=t} Th_{id}^{X} = 4 \tag{33}$$

$$k_{id}^{t+1} = k_{id}^{t} - \frac{3(k_{id}^{t+2} - k_{id}^{t})}{4} \tag{34}$$

$Th_{id}^{X} = 0$

Once the location is modified, the value of judgment is set to '0'. The position update is arbitrary. Hence, the random factor is not added.

In addition, CH selection and sink mobility are presented in **Fig 3.**

Thus, the proposed EPSO-based sink mobility strategy determined optimal points in the network trajectory over which they wait for a temporary period when they move from one region to another. This sink mobility is completely achieved by EPSO depending on factors of energy, location, load to be balanced in the network.

IV. FINDINGS AND ANALYSIS OF SIMULATION RESULT

In the first section of the inquiry, suggested HCSPSO mechanism and baseline FFBSOA, GSMRP, BFFOA and FUFOA methods are evaluated based on consisting of numerous sensors throughout the system.

During the initial phase of the examination, HCSPSO-CHS mechanism and baseline FFBSOA, GSMRP, BFFOA and FUFOA methods are evaluated according to their PDR (Packet Delivery Ratio), system longevity, message latency, and energy usage with different sensor nodes. In specific, **Fig 4** and **Fig 5** demonstrates the PDR and the network lifespan realized during implementation of HCSPSO-CHS mechanism and baseline approaches with systematic increase in points. Enhancement of PDR is mainly due to the adoption of EPSOA with aided in finding ideal locations for sinks may be deployed for temporary time to achieve improved data delivery between CHs and the sink node.

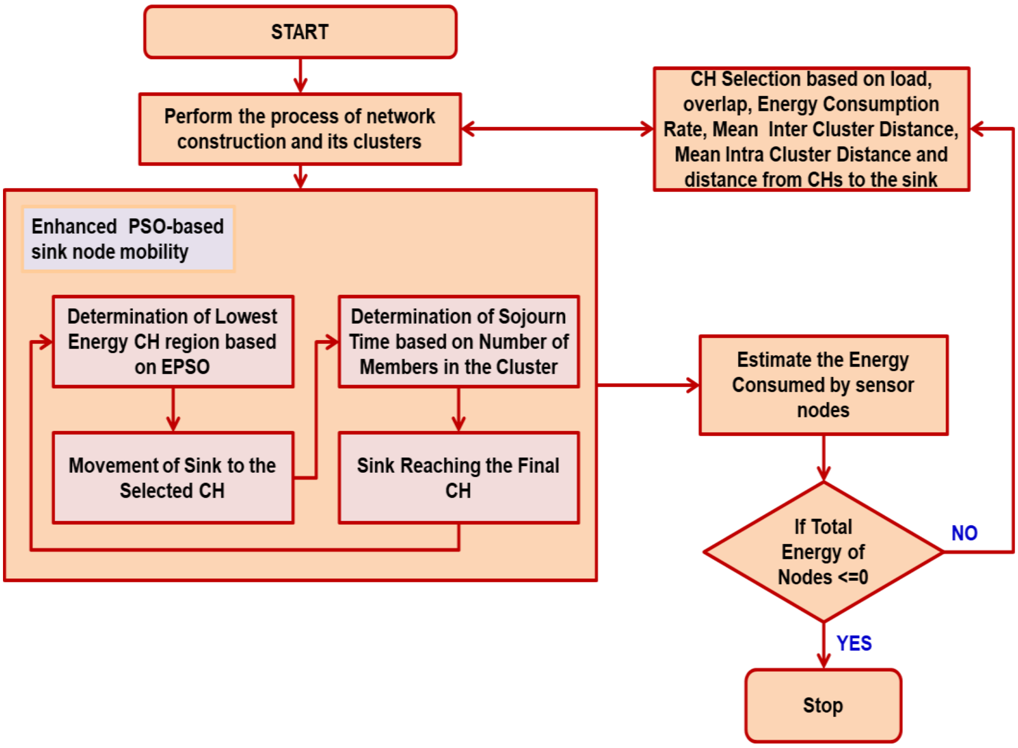

Fig 3. Process of CH Selection And Sink Mobility using EPSO Scheme

At the same time, the inclusion of CSA algorithm helped in selecting energy predominant sensor nodes as CHs and prevents worst fitness sensor nodes from being chosen as CHs. The results confirmed that the proposed HCSPSO-CHS mechanism is potentially improved the PDR by 16.82%, 18.61%, 20.98% and 22.74%, superior to the standard methods. Furthermore, network lifetime achieved during implementation of proposed mechanism is predominantly improved by 16.98%, 17.21%, 19.56% and 20.96%, greater compared to the foundational methods.

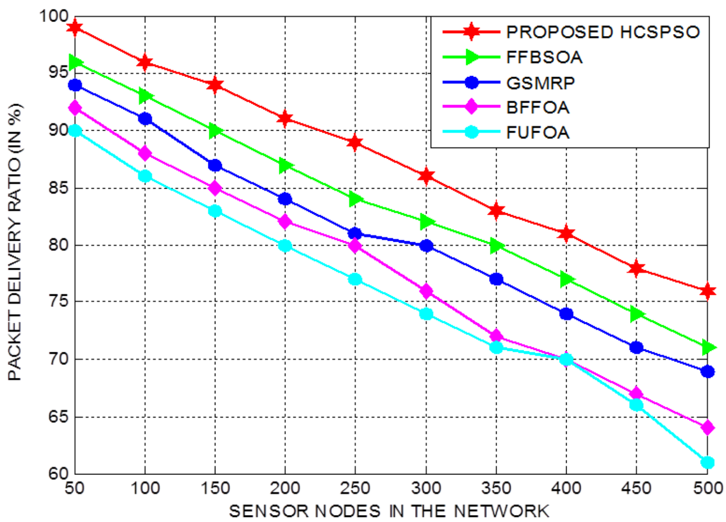

Fig 4. PDR for Varying Number of Sensor Nodes

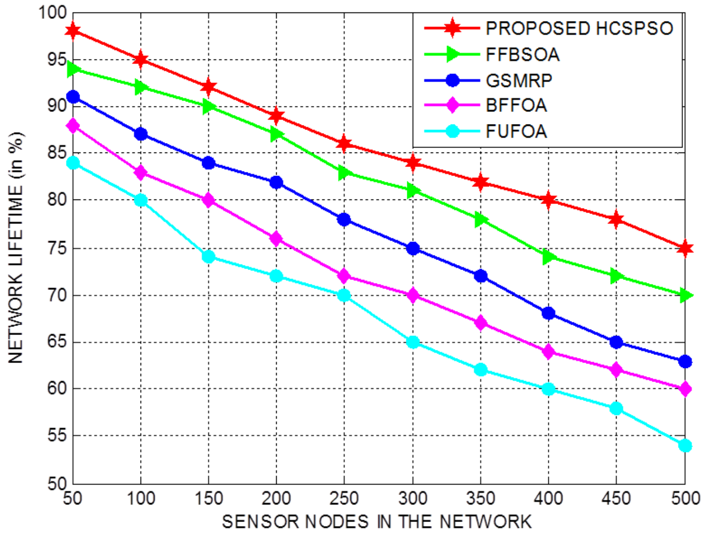

Fig 5. Network Lifetime for Varying Number of Sensor Nodes

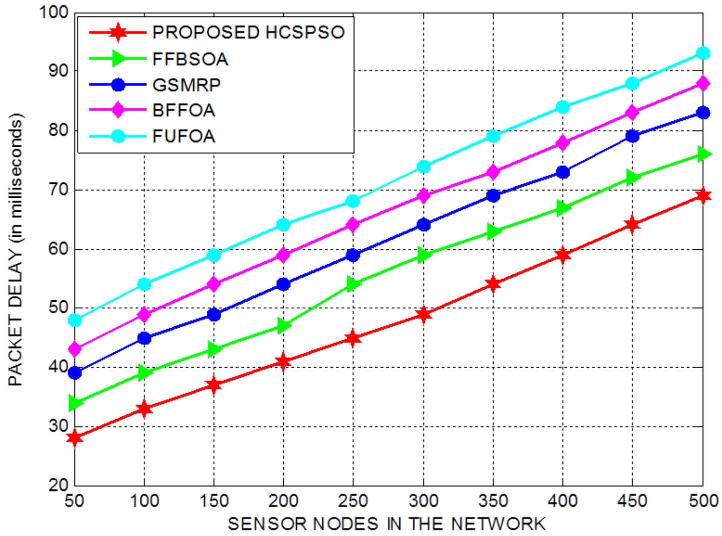

Fig 6. Packet Delay for Varying Number of Sensor Nodes

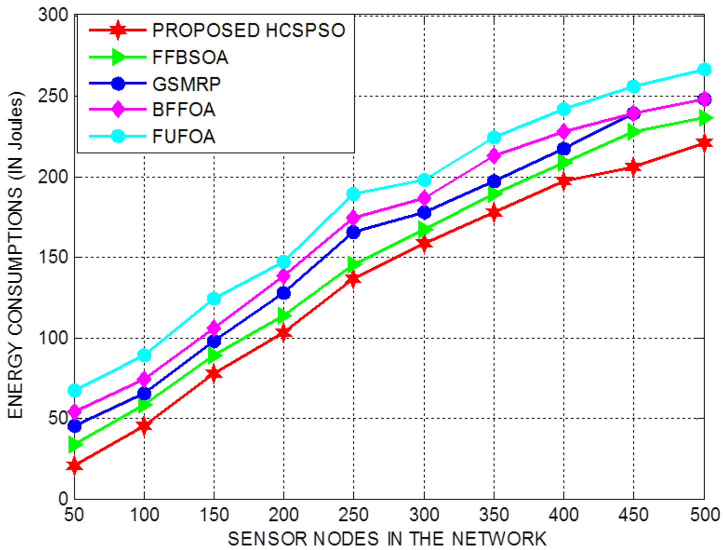

Fig 7. Energy Consumptions for Varying Number of Sensor Nodes

Further, **Fig 6** and **Fig 7** exemplars packet delay and energy consumptions incurred during the implementation of the HCSPSO-CHS scheme and baseline approaches with systematic increase in the devices equipped with sensors within the system. This proposed CH selection considerably minimized the packet delay by considering the parameter of distance estimated between CHs for each cluster, and distance between CH and the sensor node members existing in each cluster into account. Instead, the networks' energy usage is also minimized due to the incorporated of EPSOA-based sink mobility which balances energy by making the sink to move in required region at specified time to prevent unnecessary energy drain into the network. The transmission latency experienced in the execution of the suggested HCSPSO-CHS mechanism is considerably minimized by 15.28%, 18.41%, 20.92% and 22.86% better than standard approaches. Moreover, the energy consumed during implementation of proposed HCSPSO-CHS mechanism is reduced considerably by 17.21%, 19.56%, 20.96% and 22.54% in contrast to baseline approaches.

In the following stage of inquiry, the beginning and suggested method are examined FFBSOA, GSMRP, BFFOA and FUFOA methods are assessed based on PDR, network lifetime, packet delay and energy consumptions for varying number of sensor nodes. In specific, **Fig 8** and **Fig 9** depict the network stability index and throughput achieved during the implementation of the HCSPSO-CHS mechanism and the baseline FFBSOA, GSMRP, BFFOA and FUFOA approaches with different network lifetime (Rounds).

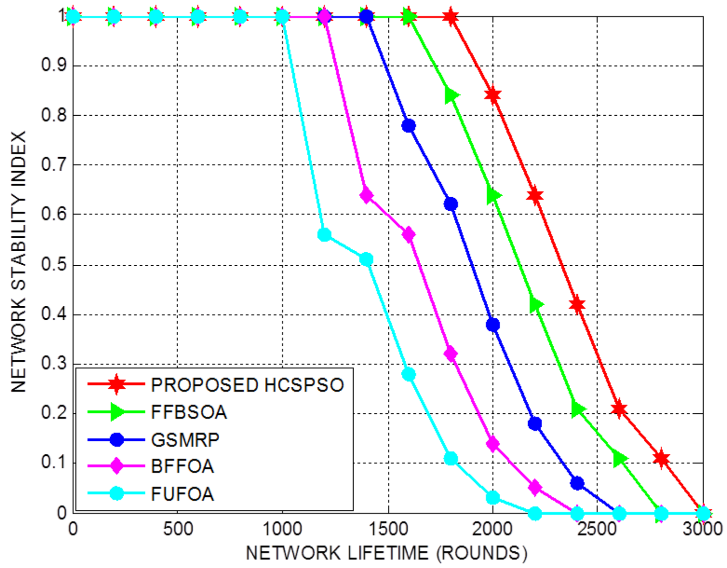

Fig 8. Network Stability Index with Network Lifetime (Rounds)

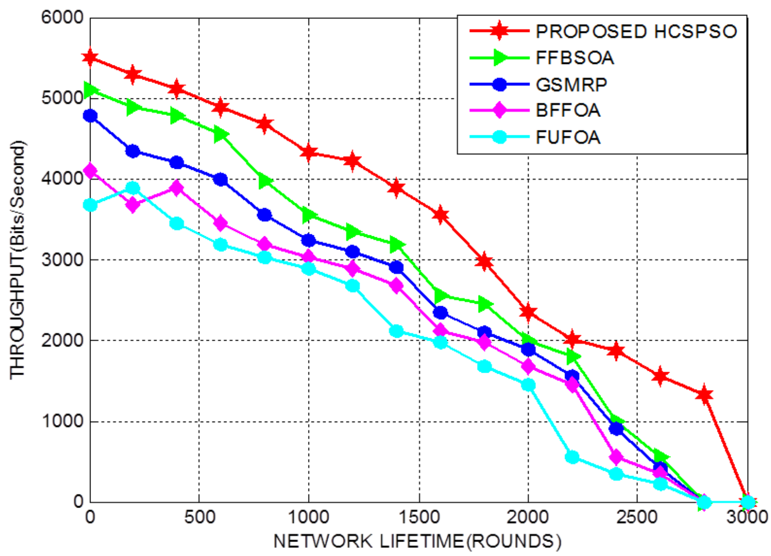

Fig 9. Throughput with Network Lifetime (Rounds)

This proposed CH selection scheme enhanced the network stability rate at a significant rate, since it selected only sensor nodes with high energy, inter-cluster distance, intra-cluster, node degree, and node centrality into account during the clustering process. It also facilitated unequal clusters in the network for preventing hot zone issue in the network.

This process of handling hot zone adopted by the proposed CH selection process aided in improving the throughout to the expected level. Hence the network stability index of proposed HCSPSO-CHS mechanism is significantly maximized by 19.21%, 17.64%, 15.98%, and 13.26%, excellent to the baseline approaches. At the same time, the throughput attained by the proposed HCSPSO-CHS mechanism with different network lifetime (rounds is reduced)is considerably improved by 23.18%, 21.34%, 19.86% and 16.52% in contrast to baseline approaches.Further, the quantityconsisting of both functioning and non-functioning nodes determined during implementation of proposed and baseline approaches are plotted using **Fig 10** and **Fig 11**. The proposed HCSPSO-CHS mechanism sustained maximized quantity of alive nodes in the network by adopting CSA which is improved in the dimensions of Probability of Self-Adaptive Perception and enhanced crossed pollination of FPA into the classical CSA for choosing energy potential sensor nodes as CHs. This energy and distance aspect consideration while developing wellness feature helped on sustaining the lifespan of nodes, thereby maintain network lifetime to desired level. Thus, the number of alive nodes is improved by proposed HCSPSO-CHS mechanism to the expected level by 26.54%, 24.12%, 23.48% and 22.86%in comparison to the standard methods. In addition, the quantity of sensor nodes prevented from death by proposed HCSPSO-CHS mechanism is improved by 23.14%, 21.86%, 19.52% and 17.62% better than standard approaches.

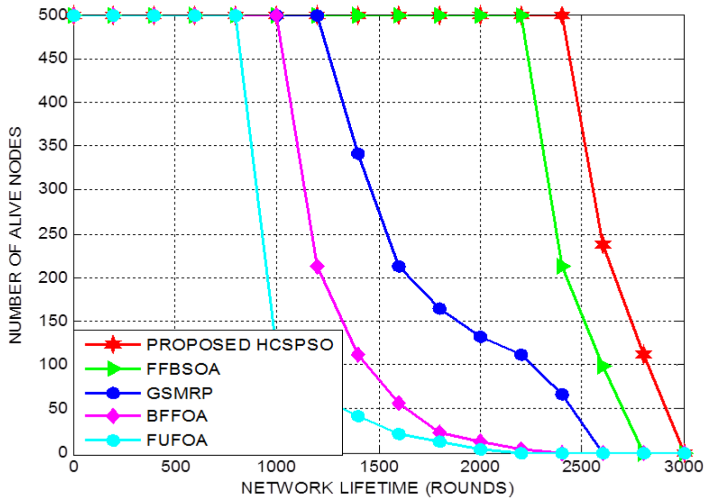

Fig 10. Number of Alive Nodes with Different Network Lifetime (Rounds)

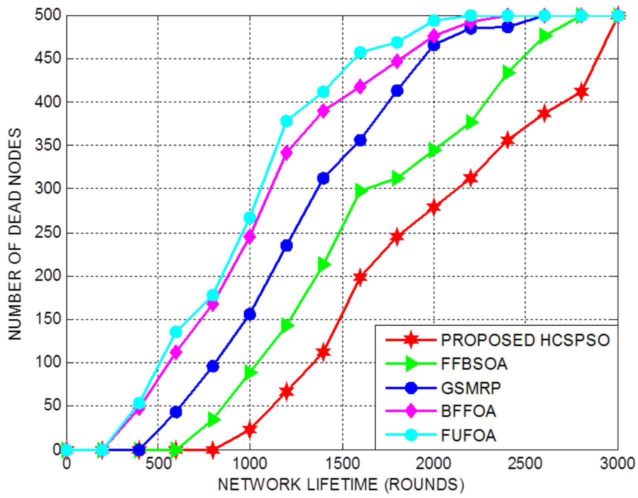

Fig 11. Number of Dead Nodes with Different Network Lifetime (Rounds)

During this third phase of the inquiry, the suggested HCSPSO-CHS mechanism and the baseline FFBSOA, GSMRP, BFFOA and FUFOA approaches are assessedin terms ofnetwork lifetime (Rounds) and Mean data packets received by the sink at FND, HND and LND. In all the cases, the network lifespan of HCSPSO-CHS mechanism is identified to be prolonged as it explored the feasible dimensions of all the comprehensive factors that contributes towards better CH selection and optimal sink mobility as portrayed in **Fig 12** and **Fig 13**. It also delivers maximized number of packets to the sink, since it used the suitable and ideal fitness factors during the process of sink mobility. It also explored the entire search space in a more exhaustive manner to prevent unnecessary process of clustering which may happen frequently due to the selection of worst sensors that use less power as CH within the system. Thus, the proposed HCSPSO-CHS mechanism during its deployment in the network prolonged the lifetime by 18.32%, 21.84%, 24.28% and 26.54% in comparison to the foundational methodologies. Furthermore, the quantity of data packets delivered to sink under implementation of the proposed HCSPSO-CHS mechanism is improved by 16.86%, 19.34%, 21.39% and 23.41% in contrast to baseline approaches.

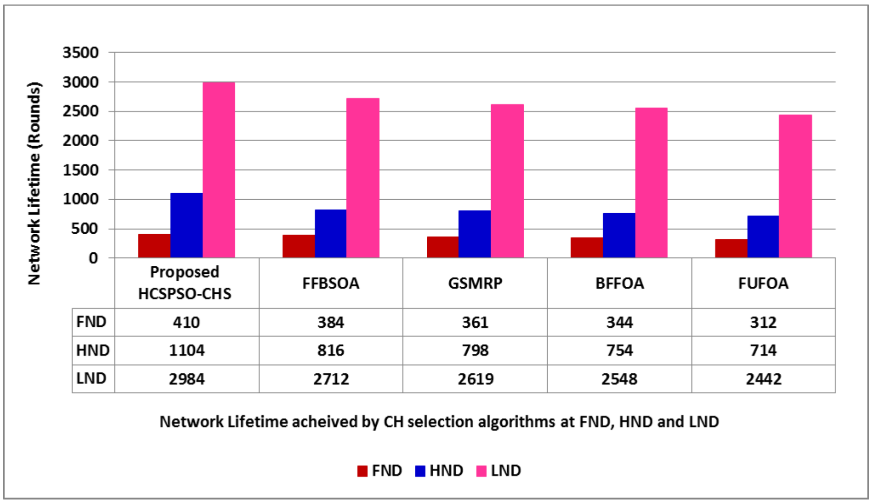

Fig 12. Network Lifetime (Rounds) Achieved at FND, HND and LND

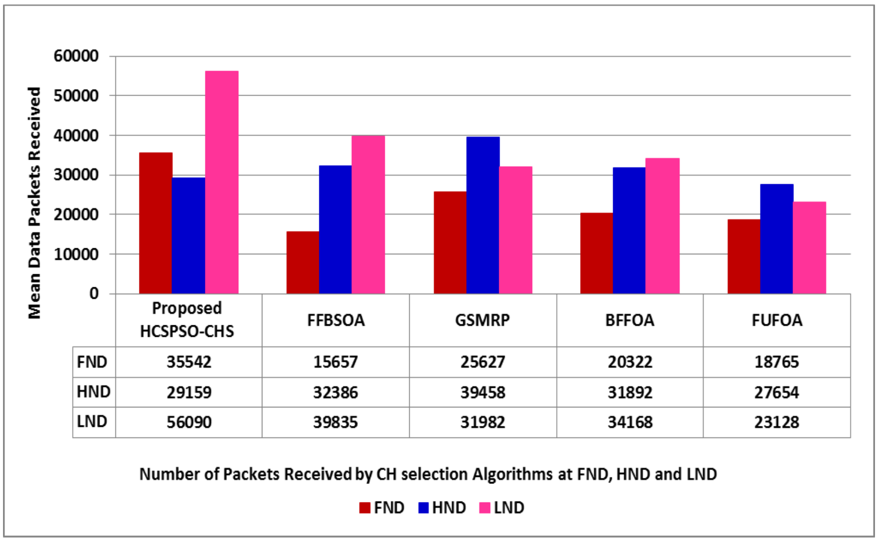

Fig 13. Mean Packets Received at the sink at FND, HND and LND Lifetime

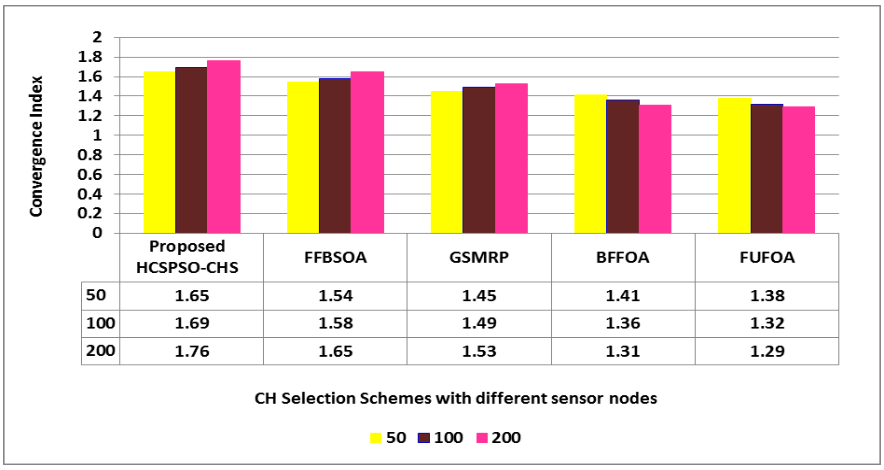

Fig 14. Convergence Index

In addition, **Fig 14** represents the convergence Index achieved by HCSPSO-CHS mechanism and baseline FFBSOA, GSMRP, BFFOA and FUFOA approaches. The proposed HCSPSO-CHS mechanism with different sensor nodes and varying energy possessed by each node is identified to exhibit maximized convergence index on par with the baseline schemes, since it incorporated the chaotic maps features into CSA for the objective of achieving significant exploitation in the search space. Thus, convergence rate reached by the proposed HCSPSO-CHS mechanism is considerably improved by 14.58%, 16.92%, 18.94% and 20.52% when compared to baseline schemes used for comparison.

V. CONCLUSION

The proposed HCSPSO-CHS mechanism integrated the potentiality of enhanced FPA-improved CSA algorithm for CH choice and EPSOA for sink movement, and, achieved extended power consistency in WSNs and the longevity of the system. This HCSPSO-CHS approach assessed the influential factors likeleftover energy, distance inside and between clusters node degree and node centrality during CH selection. It integrated FPA into the traditional CSA to facilitate better search process which attributes towards better exploration and exploitation that aids in achieving maximized convergence towards the best global solution, in order to avoid the usual choice of CHmaximum extent possible. It also adopted opposition-based learning strategy in the exploitation phase of the hybrid algorithm to avoid the selection of ineffective nodes for sensors for cluster heads (CH). The simulation results confirmed that proposed HCSPSO-CHS mechanism prolonged the network lifetime by 18.32%, 21.84%, 24.28% and 26.54% in contrast to baseline approaches. Furthermore, the quantity of data packets delivered to sink under implementation of proposed HCSPSO-CHS mechanism is improved by 16.86%, 19.34%, 21.39% and 23.41% when compared to baseline approaches. As an aspect of our future plans, it has been determined to formulate a Dingo Optimization Algorithm-based CH selection mechansim with security enforcement using homomorphic encryption scheme for securing information is sent via the chosen channel to the receiver.

Data Availability

No data was used to support this study.

Conflicts of Interests

The author(s) declare(s) that they have no conflicts of interest.

Funding

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Competing Interests

There are no competing interests.

Authors' contributions

VKP- Formulated the Problem, Literature Review, Implemented, Experimental Validation, Written; VK - Reviewed the Complete Manuscript.

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