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PARAMETERIC COMPARATIVE ANALYSIS OF CHAOTIC BEE COLONY OPTIMIZATION AND PROFICIENT BEE COLONY CLUSTERING PROTOCOL FOR ENHANCING LIFE SPAN OF WIRELESS SENSOR NETWORKS

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Abstract- Energy consumption is one of the most critical issues that needs to be addressed in wireless sensor networks (WSNs) for prolonging network lifetime. This paper discusses an optimized and effective approach, Chaotic Bee Colony Optimization (Chaotic BCO) algorithm whose main objective is to enhance the lifespan of wireless network by reducing the energy utilization among nodes. Chaotic-BCO technique used three parameters i.e. residual energy, node density anddistance for each node. These parameters aid this technique to calculate the fitness value in network to select the best cluster head(CH). The node with best fitness value is selected as the CH in that particular cluster for that iteration. Moreover, the concept of relay node has also been introduced in the proposed model which acts as an intermediate between CH and sink node for transmitting data. This relay node is chargeable and helps in reducing the burden of CH node by transmitting data from CH to sink node. The efficacy of the this approach is analyzed and validated in MATLAB software under various performance dependency factors. This paper also does the parametric comparison between Chaotic BCO and Proficient Bee Colony Clustering Protocol(PBC-CP). The results shows that the Chaotic -BCO model outperforms PBC-CP.

Keywords: Cluster Head, Chaotic Bee Colony Optimization, Wireless Sensor Network, Proficient Bee Colony Clustering Protocol, Sink Node.

I. INTRODUCTION

Wireless Sensor Network, commonly pronounced as WSN has a significant contribution in 21st century that basically incorporates a set of cutting-edge technologies like wireless communication and sensor technique that make the interaction between humans and physical world possible [17]. Moreover, WSN has been considered as one of most potent networking architectures for monitoring an IOT system. WSN is one of the keys supporting technologies in IOT systems that serves as network and routing infrastructure that underpins this powerful technology. By deploying nodes in sensing region, WSN gathers data from wide tracking areas, usually employed in smart homes, military surveillance, spaceflight, environmental sensing, as well as other IOT applications [5]. Talking about a typical WS network, huge number of small detection devices that are called as Sensor Nodes are deployed for particular purpose. These sensor nodes are responsible for collecting data from regions and transmit it to the sink node or Base Station (BS), which is basically the hub of monitoring. Unfortunately, the applicability of such sensors is restricted by their constrained energy capacity [7] and processing power. In many applications, particularly when monitoring a hostile atmosphere, replacing or even recharging the node's associated batteries is an extremely laborious task. Consequently, a key component of WSN effectiveness is power efficiency. In this regard, a number of approaches have already been suggested by various researchers. The studies have demonstrated the importance of routing protocols in conserving energy of sensor nodes. Among the various techniques, the clustering routing approach is applied widely in wireless networks as it provides benefits like, flexibility, sharing of resources, and energy conservation [11]. The clustering protocol effectively utilizes and manages the energy of sensor nodes which ultimately enhances the lifespan and efficiency of WS network [2]. The sensors present in the clustering technique are grouped together to form clusters on the basis of some specified parameters. This is followed up by the selection of CH in each cluster among the nodes present in cluster. The generic framework of the WSN with clusters is shown in figure 1.

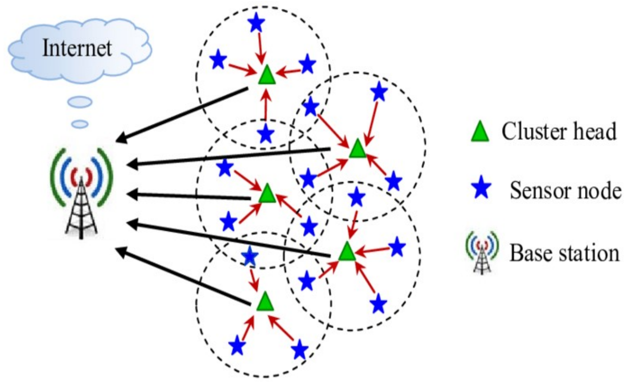

Figure 1. Cluster based WSN network

As shown in figure 1, clusters are formed in WSN network and in each cluster, there is one CH and various sensor nodes interconnected. The basic task of the CH node is to gather information from all the nodes present in that cluster and transmit it over to the BS or sink node. However, selecting a proper and appropriate CH in the network is one of the challenging and critical tasks to be performed. Since, CH node has to collect data from nodes, aggregates it and transfer it to base station, therefore it consumes a major portion of energy [12,18]. This illustrates that a single node cannot continually play the role of CH, as it is an energy-intensive activity. Hence, it is important to change CH's inaccurate intervals. In order to combat this task, a number of protocols have already been proposed by wide number of researchers [7]. The Low Energy Clustering Hierarchy (LEACH), proposed by Heintzelman and other is one of the commonly employed clustering approach, wherein CHs are selected randomly by suing probabilistic technique. Following CH selection, neighboring nodes are broadcasted info by CHs to form clusters. When adjacent nodes receive the data, they choose the closest CH to participate. After this, each member node present in the cluster sends data to its respective CH[5]. Although, LEACH increases network energy consumption, but there are some drawbacks to it as well. Among the various drawbacks, reduced network lifespan is significant one. The LEACH protocol doesn't analyze any parameter while selecting CH, which may result in selection of CH with least residual energy, thereby causing reduced network lifespan. Moreover, the uneven distribution of CHs due to the random selection, in LEACH protocol also hinders its efficacy [15,10].

Although, it has been analyzed that selecting an appropriate and effective CH in the network is an optimization problem and NP-hard problem which can only be addressed effectively by using nature inspired metaheuristic optimization methods. These optimization algorithms search for the best solution in the search space. Though there are few algorithms that favor local search, while others favor global search approaches. By taking into account different factors or indicators connected to the problem statement, the target function is created. Metaheuristic based optimization algorithms are further divided into two types of population based and single solution based [16]. The Single-solution-based searching is limited to local results since it is exploitation-oriented for refining solutions. On the other hand, population-based search technique is entirely focused on exploration phase, which refers to global optimum solution. Simulated annealing and Tabu search are examples of approaches based on a single solution. While as, population-based methods can further be divided into two types, those are; evolutionary and swarm methods. Example of evolution-based optimization algorithm is Genetic Algorithm (GA) and Differential Evolution (DA). Particle swarm optimization (PSO), Ant colony optimization (ACO), Artificial bee colony optimization (ABC), Bacterial foraging optimization (BFO), Cuckoo search, and Firefly method are examples of swarm intelligence techniques. In addition to this, a variety of other optimization techniques, including WOA, GWO, TLBO, and others, can be applied in WSN to lower node energy usage and prolong the longevity of the network.

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II. LITERATURE REVIEW

In the last few years, a number of optimization-based CH selection models were proposed by various researchers for reducing energy consumption and prolonging network lifetime. Some of the recent publications in this context are discussed in this paper.

Pathak, Aruna, et al. [8], Proposed an effective clustering approach wherein they utilized Artificial Bee Colony (ABC) for selecting CHs in the network. For selecting CH node in the network, their suggested technique analyzed parameters like residual energy, node degree and distance. Moreover, the suggested scheme utilizes an energy efficient route for transferring data from CH node to base station. Through extensive experimentation, the usefulness and efficacy of proposed approach is proved.

Singh, Jainendra, et al. **[1],** Proposed an energy saving protocol that was based on fuzzy and GWO techniques. the efficacy of the suggested approach was analyzed and validated by comparing it with traditional LEACH, HEED, MBC and FRLDG methods in MATLAB 2021b software. Furthermore, it was revealed that suggested method was able to reduce energy utilization of nodes by up to 37.5%, 33.3%, 16.6%, and 6.25% than existing techniques. In addition to this, the suggested scheme was outperforming traditional models in terms of their throughput, BER, end to end delays and PDR as well.

Xu Huibin et al. [12], Offered an efficient clustering -based routing protocol for WSN and named it as energy consumption optimization-based clustering routing (ECOR). The authors gridded the network by hexagons which comprises of one CH node only for making the distribution even. The authors used nodes residual energy and distance from center of hexagon as two important factors for selecting the CH in the network. Furthermore, they also used the Dijkstra algorithm for finding the shortest route among CHs for transmitting data to the sink node. Through extensive experimentation, it has been observed that their suggested scheme outperformed Improved LEACH model in terms of energy utilization and CH distribution.

N. A. Al-Aboody et al. [19], Proposed a three layered based hybridized clustering method for enhancing the lifespan of WSNs, in which they used GWO optimization algorithm. at the very first layer, centralized approach based on BS was utilized for selecting head node. At the second layer of their model, GWO model was utilized for finding the optimum route to transmit data from CH to sink node. Finally at third level, a distributed clustering model that was based on cost function was suggested. The suggested approach showed effective results when compared with few existing models.

Elhoseny, Mohamed, et al.[9], Proposed an efficient and effective method for reducing the energy usage of nodes and prolonging network lifespan wherein they used Improved PSO and GWO algorithms for selecting CHs and finding routes in the network. The results simulated that suggested hybrid optimization scheme was generating more effective and efficient results than traditional models in context of network lifetime and energy usage.

N Lavanya, et al. [6], Presented a model in which they used hybrid GWO that was based on Sunflower optimization (HGWOSFO) and analyzed some constraints like energy spent and distance in order to select CHs in the network appropriately. The two optimization algorithms were used for balancing the exploration and exploitation phase for enhancing the network lifespan and efficiency of model. The results showcased that suggested model yielded high performance results of around 28.58% than GWO, 31.53% than SFO and 48.8% than PSO models.

Zhao, Xiaoqiang, et al [16], Proposed an efficient model specifically for heterogenous WSNs in which they used modified GWO algorithm. The authors of this paper selected CHs in the network on the basis of initial weights. Through extensive experimentation, it was analyzed that proposed approach was performing better than conventional models like SEP, DEEC, Modified SEP and fitness value based Improved GWO by around 55.7%, 31.9%, 46.3%, and 27.0%.

M Nageswararao et al. [3], Proposed a new method for enhancing the longevity of WSNs wherein they used Moth Levy based Artificial Electric Field Algorithm (ML-AEFA) along with Customized GWO algorithm for selecting

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appropriate CHs in the network and transmitting data. The authors considered parameters like energy, node degree, distance of sensor nodes, distance from SN to BS and node death for selecting CH in the network. The results simulated that proposed model is more effectively enhancing network lifespan than other models.

Yang, Yang, et al. [4], Proposed a model for UWSNs in which they used two optimization models like Chimp Optimization along with Hunger Games Search (ChOA-HGS) algorithm in order to form clusters and finding route via multi-hopping respectively in the network. The efficacy of the suggested model was validated under different scenarios and in each scenario suggested model showed good results in terms of network lifespan and energy utilization.

Mittal, N. et al. [14], Presented an effective energy efficient routing approach in which fuzzy extended GWO algorithm that was based on threshold-sensitive energy-efficient was used. The main objective of this work was to enhance the stability of WS network. Experimental outcomes revealed that suggested model outperformed existing clustering approaches in terms of their energy usage, stability and network lifespan.

After analyzing the literature given in the above section, we came to conclusion that a significant number of researchers are trying to enhance the lifespan of wireless sensor network by introducing different approaches. However, current WSN technologies are not generating effective results when it comes to energy utilization and network lifespan. It was also observed that a major portion of energy is consumed by CH nodes while collecting and transmitting information to sink node. Therefore, it is necessary to select and utilize the energy of CH node effectively. From literature, we analyzed that existing model utilized very few parameters for selecting CH in the network, however, there are number of factors that affect the CH selection method. In addition to this, researchers used those optimization methods that get trapped in local minima while searching for global fitness value. Keeping these limitations in mind, the authors realized the need for introducing new and effective energy protocol for wireless networks.

Chaotic-Bee Colony optimization

In order to overcome the limitations of WSN, a new and effective energy efficient approach, Chaotic-Bee Colony optimization (BCO) algorithm have been discussed.This technique is also referred as Chaos Artificial Bee Colony (Chaos-ABC) algorithm. The main objective of this work is to reduce the energy consumption of nodes so that its overall lifespan of network is increased. In order to select the CHs effectively, this model utilized BCO optimization algorithm. The fundamental and key concern for integrating chaotic map along with BCO optimization algorithm is to enhance the convergence rate. Moreover, the BCO optimization model tends to get trapped in local minima, which is efficiently neutralized by chaotic map. The Chaotic-BCO wireless network helps in selecting the CH in the network by analyzing three important parameters which includes; residual energy, node density and distance for each node. These parameters are then analyzed and fitness function is calculated. The node with the best fitness value in correspondence with above mentioned three parameters is selected as CH in the network.

In addition to this, the technique enhances the performance of WSN by modifying communication phase as well. As mentioned earlier, that CH nodes need to travel larger distances for collecting and transmitting information to sink node, which results in high energy consumption that shortens network lifespan. In order to overcome this limitation, we have introduced relay node in this work that acts as an intermediate between CH and Base station. By doing so, the communication process becomes more reliable and effective and also prolongs network lifespan. The step by step working of the Chaotic-BCO approach is also discussed.

III. METHODOLOGY

The Chaotic-BCO wireless network implements a series of steps like network initialization, CH selection, data collection, data transmission with relay node and rotation of CH node.

Network Initialization: The very first step that is to initialize network in which various parameters like sensing region, total nodes to be deployed, BS location and residual energy are defined. Other than this, there are few other parameters that are defined in the network and are mentioned in table 1.

Table 1: Network Initialization Parameters

Parameter	Values
Sensor area	100*200m
Location of sink node	50, 150
Number of nodes (s)	100
Initial node energy (E_{int})	0.5
Data packet length (L) bits	4096
Energy/bit absorbed in transceiver circuitry E_e (nJ/bit)	70
Energy/bit absorbed in power amplifier E_{fs} and E_{tg} (pJ/bit/m^2)	120 & 0.0013
Energy data aggregation Eg (nJ)	5
Total iterations	3500

Node Deployment: This is the next step where the nodes are deployed in the sensing region in order to attain the coverage area. Here, a total of 100 nodes are placed in the sensing region randomly and position of sink node is (50, 150).

Cluster Formation: The next step that is cluster formation. In this phase, temporary CHs are selected in the network, then these CH act as centroid for grouping closest sensor nodes together.

CH selection using Chaotic-BCO: Once clusters are formed, the next step is to select CH in each cluster. In order to do so, Chaotic-BCO model is initialized with different parameters that are given in table 2, along with their specific values.

Table 2: Chaotic-BCO initialization parameters

Parameter	**Value**
Population (Colony Size)	20
Iteration	10
Onlooker Bees	20

The Chaotic-BCO technique analyzes residual energy, node density and distance of each node present in the cluster for calculating its fitness value. The Chaotic-BCO model examines these parameters and generates fitness for each iteration. The node with best fitness value is chosen as CH in a particular cluster.

Recruiting Cluster Members: In this phase of model, the selected CHs broadcast information to all non-CH members present in the network. The non-CH members then make a decision to join a particular CH, depending on signal strength to form final clusters in the network.

Data Collection: Soon after this, the data collection phase starts wherein the selected CH gathers information from all nodes present in the cluster and processes it before sending it to base station. In addition to this, the CH compares the information collected from sensor nodes to its own data for removing any redundancy.

Communication: After this, the communication phase begins wherein the CH is supposed to send data to the base station. However, in this work, relay node has been introduced in the communication phase. Now, before sending data to BS, the CH node analyzes the distance to BS node and to relay node. The CH node follows the route where it has to travel least distance to transmit data to BS. This means if CH is in close vicinity of BS, then data is transmitted directly, otherwise, CH passes data to relay node which in turn transmits data to the sink node.

Rotation of CH: Once communication is completed, again the same process is opted for selecting the new CH in the network. The process goes on for a fixed number of iterations and the node with best fitness value will be selected as CH for next iteration.

Performance Evaluation: In the last step, the efficacy of Chaotic-BCO model is examined and validated in the MATLAB software under different performance metrices.

Parametric Comparative Analysis

The efficacy and usefulness of the Chaotic-BCO based WSN model is analyzed and validated in MATLAB software, by comparing it with PBC-CP. The simulating outcomes were determined in terms of factors like, dead nodes, alive nodes, remaining energy, throughput and lifetime evaluation. This section presents a brief discussion and description of results attained in this regard.

In order to prove the effectiveness of the Chaotic BCO, we evaluated its performance with conventional models in terms of dead nodes. The comparison graph obtained for the same is shown in figure 2. After analyzing the given graph, it can be concluded that conventional HSA-PSO (work prior to PBC-CP)and PBC-CP models are showing least efficacy as nodes start dying after performing just around 1500 and 1600 rounds and last only up to around 1650 and 2500 rounds. Whereas, in case of the Chaotic-BCO model nodes start dying at 1700th round but still some nodes are able to communicate till 3250th rounds. This shows that lifespan of this technique is enhanced by around 800 rounds.

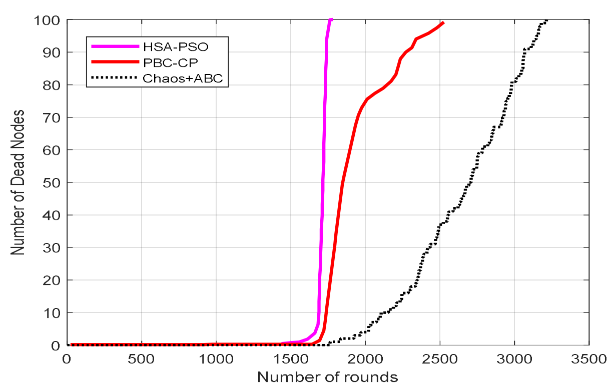

Figure 2. Comparison Graph for Dead Nodes

Moreover, the performance of the Chaotic-BCO model is also examined and validated by putting it in comparison with traditional HSA-PSO and PBC-CP models in terms of their alive nodes. Figure 3 represents the comparison graph for the same, wherein x-axis and y-axis represents the total number of rounds and alive nodes in different models. The graph reveals that nodes are alive in traditional HSA-PSO and PBC-CP models only till around 1600 and 1700 simulation rounds. While as, in Chaotic-BCO model the nodes are able to retain and preserve energy till 1750 iteration. This shows the efficacy in this paper approach over other existing approaches.

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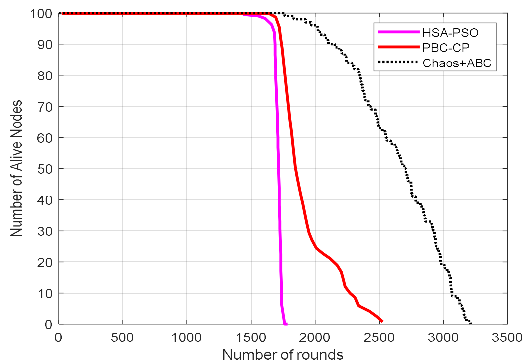

Figure 3. Comparison for Alive Nodes

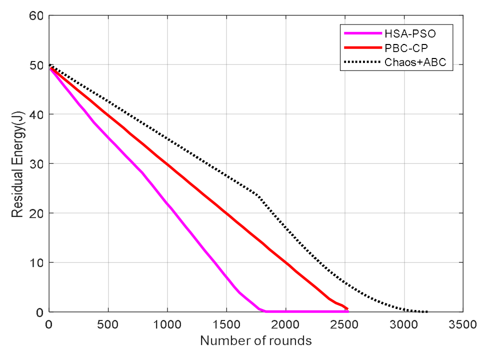

Figure 4. Comparison Graph for Residual Energy

Similarly, the usefulness of the Chaotic-BCO model is also analyzed and compared with existing models in order to determine their residual energy with respect to iterations. The solid red and pink lines determine the performance of traditional HSA- PSO and PBC-CP models whereas, dashed black line determine the efficacy of the chaotic-BCO model. From the given graph, it can be concluded that traditional HSA-PSO model shows worst results with energy depleting from 50j to 0j in just around1800 rounds. This is followed up by the conventional PBC-CP model where zero energy remains at 2500th round. However, when talking about the Chaotic-BCO model, we see that there is a considerable increase in remaining energy of nodes as some nodes still have few joules of energy after performing around 3250 rounds. These figures show that energy last effectively much more rounds in chaotic-BCO approach when compared with HSA- PSO and PBC-CP .

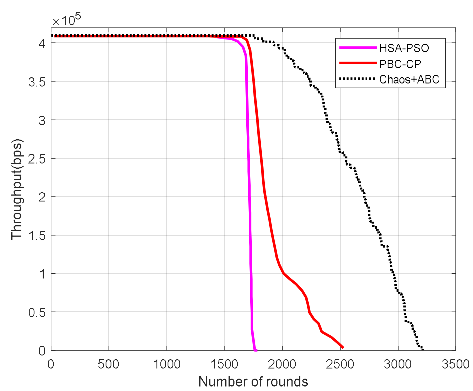

Figure 5. Throughput Comparison Graph

Figure 5 represents the comparison graph of the Chaotic-BCO model and traditional HSA- PSO and PBC-CP models in context of their throughput values. The x-axis and y-axis of the graph calibrates to number of rounds and their throughput value. From the given graph, it is observed that lowest throughput is attained by traditional HSA-PSO model till around 1650 round, followed up by the PBC-CP model till around 2500 round. However, in case of Chaotic-BCO model the highest throughput of 4×10^5 is achieved till around1600 rounds but as soon as the count of iterations increase the throughput value also decreases but still is able to perform till around 3250 rounds. These figures prove that Chaotic-BCOutilizes less energy and increases throughput up to around 750 rounds then PBC-CP models.

Table 3: Dead Node Comparison Iteration Table

PROTOCOL (Dead node)	Start dying (dead node) Round no.(approx.)	All died (dead node) Round no.(approx.)
HSA-PSO	1500	1600
PBC-CP	1650	2500
CH-BCO	1700	3250

Table 4: Alive Node Comparison Iteration Table

PROTOCOL (Alive node)	All alive (alive node) Round no.(approx.)
HSA-PSO	1700
PBC-CP	2500
CH-BCO	3250

Table 5: Residual Energy Comparison Iteration Table

PROTOCOL (Dead node)	Energy depleting	All died (node node) Round no.(approx.)
HSA-PSO	50j to 0j	1800
PBC-CP	50j to 0j	2500
CH-BCO	50j to 0j	3250

Table 6: ThroughputComparison Iteration Table

PROTOCOL (Dead node)	Throughput Round no.(approx.)
HSA-PSO	1700
PBC-CP	2500
CH-BCO	3250

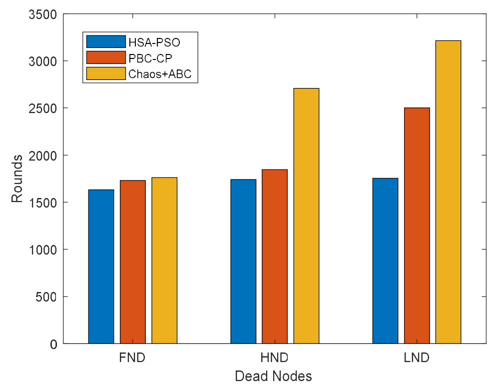

Figure 6. Lifetime Evaluation in Traditional and Chaotic-BCO

Furthermore, the efficacy of the chaotic-BCO model is examined and validated by putting it in comparison with few states of art methods in terms of their lifetime evaluation factors like FND, HND and LND. The results revealed that value of FND, HND and LND in conventional HSA-PSO and PBC-CP models came out to be 1450, 1710 & 1760 and 1642, 1845 & 2500 respectively. On the other hand, the value of FND was accounted at 1763 in chaotic-BCO model, whereas, its HND and LND values are 2709 and 3214 rounds respectively. The specific value of each lifetime evaluating parameter is recorded in tabular form also and is shown in table 7.

Table 7: Comparison for Lifetime Evaluation

Technique	FND	HND	LND
HSA-PSO	1450	1710	1760
PBC-CP	1642	1845	2500
Chaotic-BCO	1763	2709	3214

From the above graphs and tables, it can be concluded that Chaotic-BCO model is outperforming conventional HSA-PSO and PBC-CP models in all parameters and hence can be used and implemented in real world practical applications.

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IV. INTRODUCTION CONCLUSION

In this paper an optimized energy efficient energy method Chaotic-BCO that is based on Bee colony optimization (BCO) algorithm is examined in detail. The efficacy and productivity of the Chaotic-BCO model is analyzed and validated in MATLAB software under various performance dependency metrices. After analyzing the results, it was observed that chaotic-BCO model is outperforming other existing WSN approaches in terms of throughput, dead nodes, alive nodes, residual energy and lifetime evaluation. The results obtained depicts that each and every node is communicating effectively till 1700 iteration in chaotic-BCO model while as, in traditional HSA-PSO and PBC-CP model nodes start dying at 1500 and 1600 iterations. Moreover, the residual energy graph demonstrated that nodes in Chaotic-BCO model utilize less energy than traditional HSA-PSO and PBC-CP model and hence is able to communicate till 3250 iteration, while as nodes lose all energy in HSA-PSO and PBC-CP model at 1800 and 2500 rounds. Furthermore, the value for FND, HND and LND in HSA-PSO and PBC-CP model came out to be only 1450, 1710 & 1760 and 1642, 1845 & 2500 rounds. Whereas, when same factors were analyzed in Chaotic-BCO model, it came out to be 1763 for FND, 2709 for HND and 3214 for LND respectively. These values prove the efficacy and efficiency of this work over other existing approaches.

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