International Journal of Engineering Sciences Paradigms and Researches [Volume 47, Issue: Special), March 2018]
www.ijesonline.com ISSN (Online): 2319-6564

A Wireless Sensor Network's Best Cluster Head Selection Using the Combined Osprey-Chimp Optimization Algorithm (CIOO)

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Abstract— *A large amount of attention has been paid to the development of Wireless Sensor Networks (WSN) for smart systems because of its potential applications in many different fields. WSN is made up of tiny, battery-operated sensor nodes that are organized separately. The primary factors are the resources and energy consumption of sensor nodes. In particular, imbalanced nodes use more energy and have a shorter network lifespan. Energy efficiency in the selection of WSN cluster heads is still a difficult job. Clustering is the best technique that has been found for lowering node energy usage. However, without taking into account energy attributes, node quantity, or flexibility, the existing clustering technique was unable to allocate the nodes' energy needs effectively. Therefore, new optimization strategies and an enhanced clustering procedure are required.*

Keywords—Wireless sensor network; clustering; cluster head; cluster head selection; chimp optimization; osprey optimization

I. INTRODUCTION

In recent years, a wide range of application domains, including military operations, medical care, smart cities, renewable electric power and energy, with monitoring the environment, have benefited significantly from the technological innovation and research carried out on WSNs. WSN is made up of BS and many sensor nodes [1, 2]. These are tiny independent devices with many limitations, including battery life, low processing power, and short communication distance [3]. To detect or sense variations in environmental factors like temperatures, movement, stress, moisture, vibration, noise, etc., these nodes are scattered geographically over a vast region. Nodes are effective enough to speed up data transfer via wireless networks. One of the fundamental technologies of substantial WSN, data collecting has attracted major academic interest [4, 5]. The data is sent to a data sinks or BS after collection. Sensor nodes are periodically placed in dangerous locations; and in these situations, replacing the batteries is not feasible. The sensor nodes use more energy since they constantly transmit and receive data. When nodes consume too much energy, they fail and can no longer be repaired or recharged with another battery source [6]. Therefore, balancing the nodes energy is the main issue in WSN [7, 8]. In order to increase the longevity and efficiency of the network, it is essential to allocate node energy correctly and optimize node energy consumption. Networking solutions related to sustainability and efficacy are being explored for energy concerns through hierarchical clustering algorithms [9, 10]. A familiar cluster-based routing methods like Low Energy Adaptive Clustering Hierarchy (LEACH) [11], Centralized-LEACH, and Improved-LEACH significantly aids in optimizing node energy towards the network longevity [12, 13]. However, such protocols are constrained as they choose an arbitrary applicant for the CH without taking energy variables into account, and not succeed to accomplish optimal formation of clusters and CH. This resulting in exhibiting greater communication costs, route by a single hop, and consume a greater amount of energy [14, 15] leading to network lifetime extension. Also, more optimization algorithms do involve in this CHS since from its evaluation, however, few existing optimization techniques struggle to preserve the level of investigation and extraction of choosing CH since they concentrate on particular search domains. Hence, proposing advanced optimization algorithms for optimal clustering is needed, and accordingly, this paper intends to prepare a new cluster-based routing model. The main contribution of the proposed model is given below:

- Proposing a new CIOO algorithm that combines both osprey optimization algorithm and chimp optimization algorithm for the CH selection, and also determining an improved trust evaluation as the constraint for routing.
- The proposed algorithm is subjected for evaluation with the conventional algorithms to emphasis its effectiveness.

The remaining part of this research paper is structured as below. Literature review is shown in Section II. The proposed cluster head selection method is illustrated in Section III. The results and discussion are highlighted in Section IV. Conclusion and future scope of the recommended model is provided in Section V.

II. Literature Review

The latest advancements in cluster head selection in WSN are examined in this section. The authors in [16] stated that one of the most important techniques used to extended the lifespan of WSNs operated by batteries was clustering routing. However, the majority of currently used clustering techniques fail to make use of the node redundancies in WSNs, resulting in significant energy waste. The authors in [17] introduced a technique for cluster head selection in multilevel topological control that makes use of fuzzy grouping pre-processing and optimization of particle swarms. The authors in [18] created a distributed CH selection approach whereby distances among sensors and a base station were taken into account to ensure continuous optimization of energy usage among the sensors. Authors in [19] introduced a brand-new technique termed clustering-based Cluster-Head Selection Scheme with Power Control (CHESS-PC) in PSN. Authors in [20] explored the Dynamic Cluster Head Selection Methods (DCHSM) for WSN to address the problems of unreasonable cluster leader selection, which in turn results in imbalanced consumption of energy and inconsistent coverage in the cluster communications.

Authors in [21] presented an approach called LEACH to control the unpredictability that occurs in clustering algorithms. With this strategy, the cluster head count was stabilized. Authors in [22] proposed a Hausdorff clustering technique, a new static kind of cluster approach based on the arrangement of sensor nodes that also improves network interaction and effectiveness. Authors in [23] proposed the Cluster Head Selection by Randomness with Data Recovery (CHSRDR) approach, which was a new way for WSN to select the cluster head with recovered data and maintained inside the cluster. Authors in [24] created a Firefly algorithm for choosing the cluster head in a manner which was sufficiently near to the base station as well as the sensor nodes. As a result, the period of delay was significantly compact, increasing the information packets' transmission speed. Authors in [25] introduced a Particle Swarm Optimization (PSO) technique for creating energy-aware clusters by selecting the best cluster heads. The PSO has ultimately reduced the expenditure of determining the perfect place for the CH nodes.

Authors in [26] created a Fuzzy Based Balanced Cost CH Selection Algorithm (FBECS) that takes into consideration the remaining energy, distance toward the sink, and population of the node in the area as inputs to the fuzzy decision-making method. Authors in [27] introduced Hyper Exponential Reliability Factor Based Cluster Head Election (HRFCHE), an integrated prediction technique for energy and trust evaluation for extending the network's lifespan. By extending the network lifetime and decreasing consumption of energy by 28% and 34%, respectively, compared to cluster head selection systems used as a benchmark, the outcomes of HRFCHE have implied greater efficiency. Authors in [28] concentrated on the effective operation of WSN applications, proving that the energy-efficient operation of the sensors became an important framework for extending the lifespan of the network. Authors in [29] implemented a Fuzzy-TOPSIS method in Select CH effectively and efficiently in order to optimize the WSN lifetime.

Even though the literature survey deals with efficient cluster head selection methods, there is still scope to improve the overall lifetime of the network and increase the number of alive nodes. These gaps can be addressed by developing new multi-constraint-based optimal cluster head selection methods.

III. Proposed Chimp Integrated Osprey Optimization Algorithm for Optimal Cluster Head Selection in WSN

The two main obstacles in wireless sensor networks are selecting the right cluster head and energy-related constraints. In order to overcome these obstacles and extend the network's lifespan, optimized algorithms are crucial. Clustering is the most critical process for increasing network longevity in WSNs. Sensor nodes are organized into clusters, and each cluster is assigned a CH. The CHs take data from the nodes in each cluster and forward it to the base station. Choosing the suitable CH in WSNs is a major challenge. Four criteria‟s energy, delay, distance, and security are used to establish a novel cluster head selection framework in our proposed model. The suggested model is summarized as follows:

- Initially, the clustering procedure groups the sensor nodes together. The k-means clustering algorithm is used in our suggested work to perform the clustering procedure.
- After the cluster‟s development, the cluster head is selected by CIOO algorithm which combines both osprey optimization algorithm and chimp optimization algorithm.
- The new CIOO algorithm is executed with four parameters like energy, distance, delay, risk.

A. Clustering via k-means Clustering

The research community has focused heavily on clustered to address the energy, scalability and lifetime problems of WSNs. Clustering algorithms restrict connection to a local area and utilized forwarding nodes to send the essential data to the reaming nodes of the network. Generally, the cluster members do interact with the CH, and the CH collects and combines the information gathered to save the energy. Here, the cluster heads can additionally create an additional layer of clusters between them. The k-means procedure [30], which offers straightforward, extremely dependable, fast-convergent repetitions & re-clustering throughout failure conditions, is a well-liked centralized as well as spread probabilistic partitional clustering method. The clustering process in the k-means algorithm is largely dependent on Euclidian distances. The procedure for k means algorithm is explained in step-by-step procedure given below.

- Group the nodes into 'k' clusters, take 'k' centroids and arrange them initially at random locations.
- Calculate the nearest centroid by calculating the Euclidian distance among every node as well as the entire center. Initial clusters are created by this process, „k‟.
- Recalculating the locations of centroids in every cluster and any changes to be checked from the prior calculation.

- If any changes in the centroid position, then proceed to Step 2; else the clustering process is complete and finalized the clusters.

This involves grouping the nodes into 'k' clusters, and selecting the CHs for every cluster is by the hybrid optimization technique like CIOO technique, which is explained in the subsequent section.

B. *Optimal Cluster Head Selection via CIOO Algorithm*

After the clustering process, optimal cluster head is selected depends on the consideration of nodes energy, distance like inter-cluster and intra cluster distances, delay and Risk factors by using CIOO algorithm. The calculation of distance, delay and risk of the clustering nodes are explained as follows. Fig. 1 shows the architecture of CH selection via CIOO algorithm.

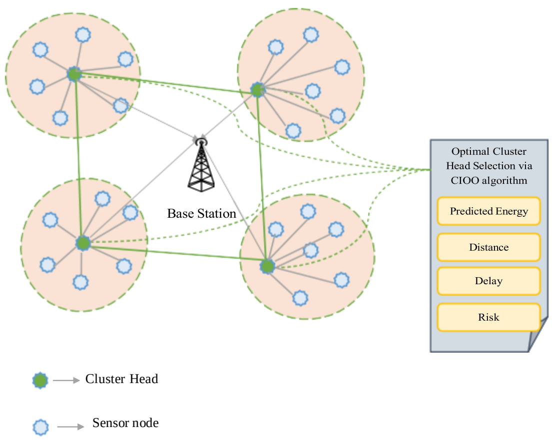

Fig. 1. CH selection framework by CIOO algorithm.

1) Distance (Δ)*:* The spacing among nodes in identical and separate clusters is measured by distance (Δ_{CH}). Here, Inter-cluster distance and intra-cluster distance are the two forms of distance that are computed. The Euclidean, Manhattan, and Chebychev distance formulas are utilized for the calculation of the distance among the cluster's nodes. Let R, S be the clusters, and their distance of each node in the cluster be $|R|$ and$|S|$, respectively. There are two distances determined by inter-cluster and intra-cluster distances are Average Linkage Distance and Complete Diameter Distance, respectively.

a) Average Linkage Distance (Inter cluster distance): Eq. (1) defines the calculation of averaged linkage distance that is the average distance between all of the nodes in two distinct clusters, where X represents the node in cluster, R and Y indicates the nodes in cluster S.

$$\Delta(R,S) = \frac{1}{|R||S|}\sum_{\substack{x\in R\\ y\in S}} d(\mathrm{x},\mathrm{y}) \tag{1}$$

b) Complete Diameter Distance (Intra cluster distance): Using Eq. (2), the whole diameter separation is determined as the spacing between two nodes in the same cluster (CH and Sensor node) which are located the furthest apart from each other.

$$\Delta(R) = \max{}^{*} d(x,y)+ \tag{2}$$

2) Delay (D)*:* When there do not exist accessible node for delaying the data, a delay constraint in a WSN is defined asthe time interval between the dispersed data of one-time unit and another. As a result, the delay is more closely related to the delay of the probabilistic transmitting system. The mathematical computation of delay, which is the ratio of distance and speed, is shown in Eq. (3), where D' denotes the distance and S' denotes the speed.

$$Delay\ (D_{CH}) = \frac{D^F}{S^F} \tag{3}$$

3) Risk (f_{ri})*:* The various elements of security methods such as risky mode, the γ-risky mode and the security mode [31] that are explained below.

a) Risky mode: This strategy selects a present CH and accepts all risks to promote an ideal CHS. As a result, choosing CH is regarded as choosing an aggressive mode.

b) γ -risky mode: The setting of the Cluster Head which can handle the maximum of γ-risk level is selected based on the "γ-risky mode." Therefore, a likelihood metrics having a value between 0 and 1 of 100% that shows the secure and risky modes is represented by the symbol γ.

c) Security mode: This option supports the CH, which fulfills with security standards in security mode. The variables R^{sd} and R^{sr} indicates the security demand and the security rank pertaining to CH selection. The node is considered to be CH if $R^{sd} \leq R^{sr}$. Security constraints is determined as shown in (4). Additionally, "the risk should be 50% below if the chosen CH achieves the stated $R^{sd} < R$. If the condition $0 < R^{sd} - R^{sr} \leq 1$ is true, the selecting process would proceed as planned rather than being delay in $1 < R^{sd} - R^{sr} \leq 2$. The state $2 < R^{sd} - R^{sr} \leq 5$ continues carrying out the related function as the CHS process unable to be completed.

$$\mathrm{f}_{risk} = \begin{cases} 0 & , \text{if } R^{sd} - R^{sr} \leq 0 \\ 1 - \frac{(R^{sd}-R^{r})}{2} & \text{if } 0 < R^{sd} - R^{sr} \leq 1 \\ 1 - \frac{3(R^{dd}-R^{r})}{2} & , \text{if } 1 < R^{sd} - R^{sr} \leq 2 \\ 1 & , \text{if } 2 < R^{sd} - R^{sr} \leq 5 \end{cases} \tag{4}$$

C. *Objective Function for CH Selection*

The objective function for CH selection is calculated depends on the minimum fitness function of constraints like nodes energy, Delay, Distance and Risk. In the proposed work, two objective functions are considered, the first objective function is based on the consideration of Risk, Distance, Delay and the second objective function is based on the consideration of Energy. The fitness and the first objective function $f_1$of Risk, Delay and Distance for CH selection is evaluated in Eq. (5) and Eq. (6), which obtained the minimum value of Risk, Distance and Delay, where,w_1 , w_2 and w_3 indicates the weight of Risk, Distance and Delay respectively. The summation of the total weight is represented as $\sum w_{\mathrm{i}} = 1$. Then the second objective function f_2 of cluster head selection under the consideration of nodes energy is determined as per Eq. (7)

and Eq. (8). Here, w_4 denotes the weight of energy, which obtain maximum in energy consumption.

$$\text{Fit} = \text{Minimum}(w_1 * f_{\text{risk}} + w_2 * \Delta_{CH} + w_3 * D_{CH}) \quad (5)$$

$$\text{obj}(f_1) = \text{Minimum}(\text{ Fit }) \quad (6)$$

$$\text{Fit} = \text{Minimum}(w_4 * (1 - E)) \quad (7)$$

$$\text{obj}(f_2) = \text{Minimum}(\text{ Fit }) \quad (8)$$

Finally, combined the objective function is mathematically defined in Eq. (9), where, m denotes the parameter in the range of [0, 1], f_1 denotes the overall objective function for the CH selection, f_1 and f'_2 are the two objective functions.

$$F' = m * f_1 + (1 - m) * f_2; \quad 0 < m < 1 \quad (9)$$

D. Solution Encoding for CH Selection

The Solution given to the CIOO algorithms are nodes. The lower bound value is fixed as 1 and the upper bound value is n, where, n denotes the number of sensor nodes. Here, the population size is allocated as 10. The flowchart in Fig. 2 shows the CIOO algorithm implementation processes.

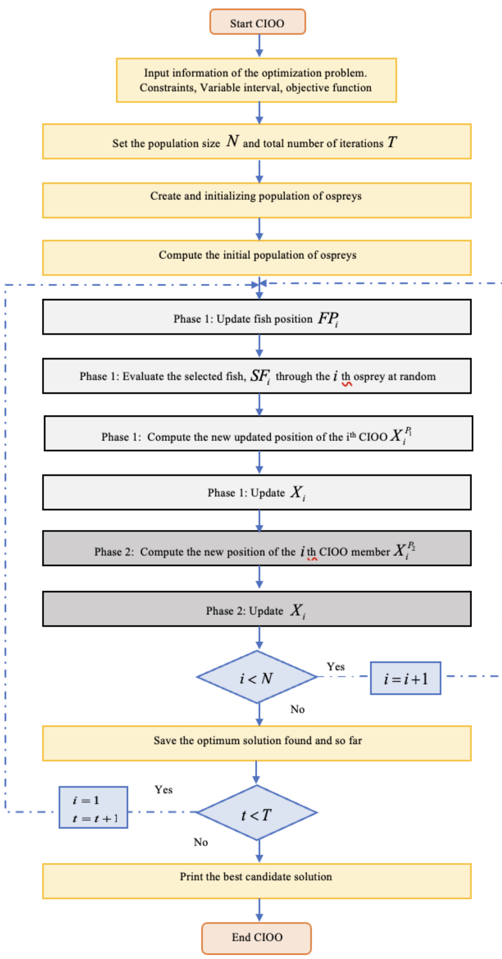

Fig. 2. Flowchart of CIOO algorithm.

IV. Results and Discussion

A. Simulation Procedure

The simulation of the proposed cluster-based routing in Wireless Sensor Networks (WSN) was conducted using MATLAB, with the MATLAB version being "Matlab R2018a."Further, the processor utilized was "Intel(IR) Core(TM) i5-1035G1 CPU @1.00GHz 1.19 GHZ" and the system had a total installed RAM size of "20.0GB," with "19.7GB" of it being usable.

B. Performance Analysis

Additionally, the performance of both the CIOO and conventional approaches was evaluated across various metrics, including Distance, Total Packets Transmitted to the Base Station (BS), Residual Energy, Delay, Alive Nodes, and Risk. Furthermore, the CIOO method was compared with state-of-the-art approaches such as DMOSC-MHRS [32] and PSO [33]. Additionally, a comparative analysis was conducted between the CIOO method and traditional algorithms, including GOA [34], SMO [35], BOA [36], COA [37], and OOA [38]. The network setup and energy model were illustrated in Fig. 3.

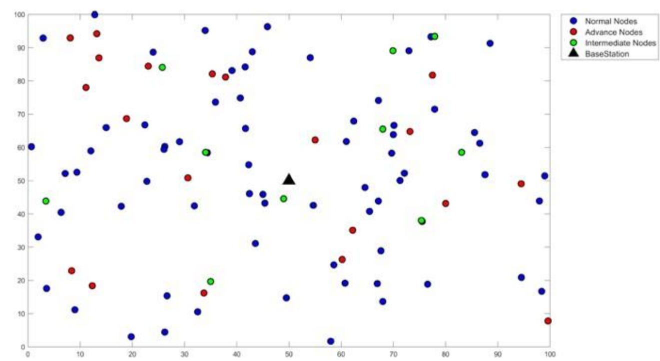

Fig. 3. Network setup.

C. Analysis on Delay and Distance

Fig. 4 and Fig. 5 provide an explanation of the delay and distance evaluation in comparison to PSO [33], DMOSC-MHRS [32], GOA [34], SMO [35], BOA [36], COA [37], and OOA [38] for the optimal selection of cluster heads. Additionally, this analysis is conducted while varying the number of rounds (500, 1000, 1500, and 2000). The objective for achieving optimal cluster head selection is to minimize both delay and distance ratings. Interestingly, at the 1000th round, the CIOO method exhibited the highest delay and distance values. However, as the number of rounds increased beyond 1000, there was a noticeable decrease in both delay and distance rates. Mainly, at the round 2000, the CIOO method achieved an impressively low delay value of 2134s. In contrast, traditional schemes recorded notably higher delay values, such as, PSO [33] =2856s, DMOSC-MHRS [32] =2150s, GOA [34] =2598s, SMO [35] =2342s, BOA [36] =2831s, COA [37] =2797s, and OOA [38] =2782s, respectively. In addition, the distance rate attained by the CIOO scheme is 8.732×104 at the round 1500, whereas the PSO [33], DMOSC-MHRS [32], GOA [34], SMO [35], BOA [36], COA [37] and OOA [38] resulted in greater distance ratings. As a result, the CIOO method employs a hybrid optimization strategy that combines

OOA [38] and COA [37] to achieve optimal cluster head selection in WSN. This method consistently achieves dependable results by efficiently decreasing both delay and distance metrics.

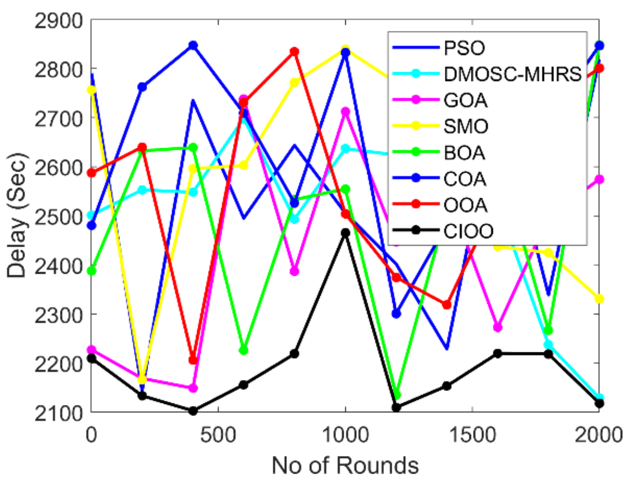

Fig. 4. Delay validation of CIOO with conventional algorithms.

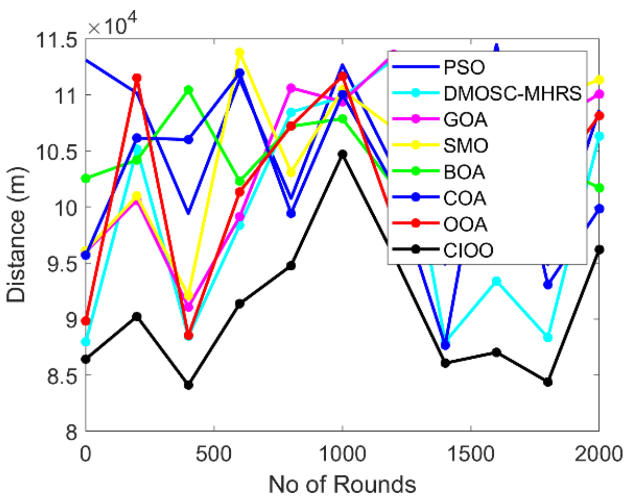

Fig. 5. Distance validation of CIOO with conventional algorithms.

D. Analysis on Alive Nodes

Fig. 6 presents a comparative analysis of the number of alive nodes in the CIOO approach versus PSO [33], DMOSC-MHRS [32], GOA [34], SMO [35], BOA [36], COA [37], and OOA [38] for cluster-based routing in WSN. In the pursuit of achieving optimal cluster-based routing in WSN, the primary goal is to maximize the number of nodes that remain active or "alive." During the initial round, both the CIOO and conventional approaches achieved the highest number of alive nodes. Nevertheless, as subsequent rounds progressed, the number of surviving nodes declined. Nevertheless, it's worth noting that the CIOO method consistently outperformed the conventional approaches by maintaining a higher number of active nodes. Significantly, the CIOO method achieved the highest number of active nodes, reaching 42 at round 2000. This count is notably superior to the numbers achieved by PSO [33], DMOSC-MHRS [32], GOA [34], SMO [35], BOA [36], COA [37], and OOA [38].

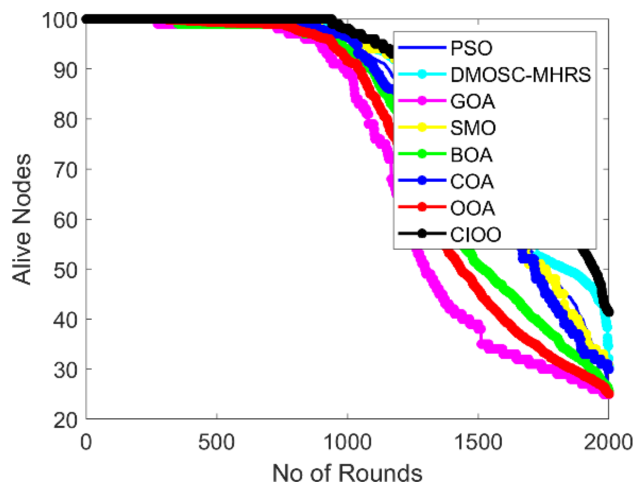

Fig. 6. Validation of CIOO with conventional algorithms on alive nodes.

E. Analysis on Risk and Total Packets Transmitted to Base Station

Fig. 7 depicts the assessment of risk associated with the CIOO method in comparison to PSO [33], DMOSC-MHRS [32], GOA [34], SMO [35], BOA [36], COA [37], and OOA [38] for the purpose of optimal cluster head selection. It is imperative to reduce the risk rate when aiming for the optimal selection of cluster heads. In this regard, the CIOO approach consistently demonstrated the lowest level of risk when compared to the conventional schemes throughout all rounds. Mainly, round=1000, the CIOO method achieved the lowest risk level of 0.012, while PSO [33], DMOSC-MHRS [32], GOA [34], SMO [35], BOA [36], COA [37], and OOA [38] exhibited higher risk ratings.

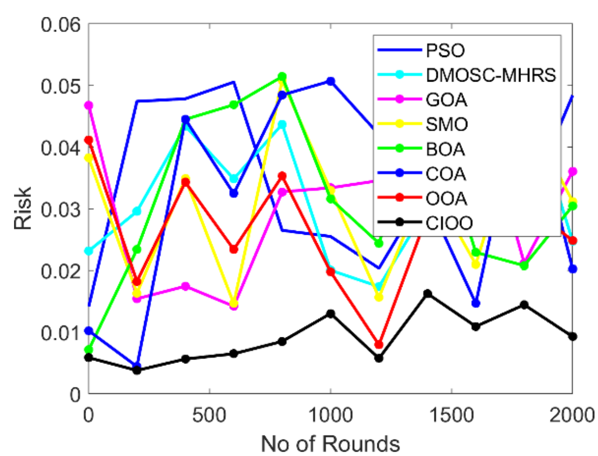

Fig. 7. Risk factor analysis of CIOO with conventional algorithms

The CIOO and conventional strategies is analyzed in terms of total packets transmitted to BS for cluster-based routing in WSN. The results of this analysis are presented in Fig. 8. Furthermore, this analysis is conducted with a network of 100 nodes, aiming to achieve the highest possible number of packets transmitted for optimal cluster-based routing. Primarily, the CIOO transmitted a larger number of packets to the BS compared to PSO [33], DMOSC-MHRS [32], GOA [34], SMO [35], BOA [36], COA [37], and OOA [38]. Hence, the CIOO approach consistently reduced risk ratings while increasing the overall number of packets sent to the BS when compared to conventional methods. In conclusion, the CIOO methodology demonstrates superior performance compared to previous approaches.

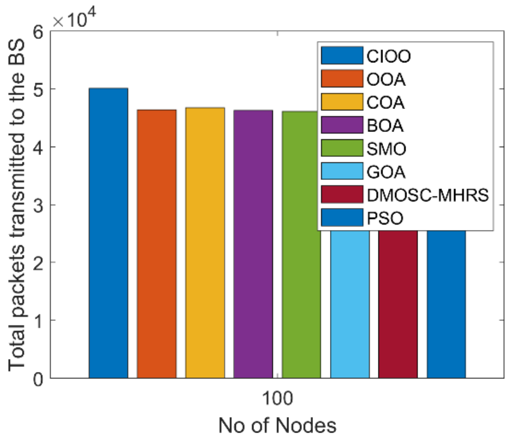

Fig. 8. Validation of CIOO and conventional schemes on total packets transmitted to base station.

F. Friedman Test Analysis

The Friedman test assessment on CIOO is compared with PSO [33], DMOSC-MHRS [32], GOA [34], SMO [35], BOA [36], COA [37] and OOA [38] for cluster-based routing in WSN is summarized in Table I. The Friedman test is a statistical hypothesis test designed for evaluating whether there exist statistically significant distinctions among various groups when analyzing correlated, non-parametric data. This test is commonly employed when dealing with multiple treatments or conditions, aiming to determine if there are overall differences in their effects. The procedure entails assigning rankings to the data within each group and subsequently assessing whether these rankings display significant variations among the groups. The presence of such variations indicates significant differences between the groups. Here, the CIOO attained the minimal value of 1, whereas the PSO [33] (5.900), DMOSC-MHRS [32] (3.500), GOA [34] (5.00), SMO [35] (6.500), BOA [36] (4.500), COA [37] (6.900) and OOA [38] (2.700), respectively.

TABLE I. ANALYSIS ON FRIEDMAN TEST

Methods	Values
PSO [33]	5.900
DMOSC-MHRS [32]	3.500
GOA [34]	5.000
SMO [35]	6.500
BOA [36]	4.500
COA [37]	6.900
OOA [38]	2.700
CIOO	1

V. CONCLUSION AND FUTURE SCOPE

This investigation proposes a new optimal cluster head selection model for WSNs based on multi constraints like delay distance security and risk. For cluster head selection, a brand new CIOO (Chimp Integrated Osprey Optimization) method has been developed. The proposed work could be evaluated with the conventional methods in terms of delay, distance, the number of alive nodes, residual energy, risk, total packets transmitted to the BS. And it is stated that the proposed CIOO method consistently outperforms against the conventional methods. These results suggest that CIOO is an effective and efficient approach for cluster-head selection in WSN, providing better network performance and energy efficiency while minimizing delay, distance and risk.

The proposed algorithm is better suited for higher-level applications where energy efficiency and the number of alive nodes are of critical concern. It may be possible to create sophisticated optimization algorithms to solve real-world problems like healthcare. Node failure detection may be an interesting security concern in the future.

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