Combined Osprey-Chimp Optimization for Cluster Based Routing in Wireless Sensor Networks: Improved DeepMaxout for Node Energy Prediction

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ABSTRACT

The significant advances in Wireless Sensor Networks (WSNs) facilitate many latest applications, such as intelligent battlefield, home automation, traffic control, and more. WSNs comprise small autonomously organized sensor nodes that are powered by batteries. The processes of collecting information and data storage, processing, and transmission deplete the energy of these small devices. Energy efficiency is still a major issue to address in WSN routing. Clustering is the best method that has been developed to reduce node energy consumption. However, current clustering methods are unable to effectively distribute the energy requirements of the nodes without considering energy characteristics, number of nodes, and flexibility. This study proposed a new cluster-based routing model for WSNs and emphasized the need for an improved clustering process with new optimization techniques. In particular, the improved DeepMaxout model was adopted to predict the energy of the nodes. Cluster Head (CH) selection is performed considering the nodes' energy as a prime factor. After choosing the CH, the CIOO algorithm incorporates new link quality and trust evaluations while determining the routing process. Finally, a comparison of energy utilization factors was performed between the suggested and traditional approaches.

Keywords-node energy prediction; improved DeepMaxout; osprey-chimp; routing

I. INTRODUCTION

A Wireless Sensor Network (WSN) is a particular type of network that encompasses many autonomous sensor nodes equipped with different sensors that track and collect information from the real world [1]. These sensor nodes are typically small, energy-constrained devices that are disseminated over a region [2]. Due to advances in WSN technology, they have significant use in different applications, such as healthcare, environment, industry applications, home automation, military, and many more [3]. The major problem of WSNs involves balancing the energy of the nodes with each other [4]. To extend the lifespan of the network and improve its efficiency, it is necessary to properly distribute node energy and optimize node energy usage [5].

To address energy-based challenges, hierarchical clustering techniques, which have advantages related to sustainability and effectiveness, are being considered as solutions for WSNs [6]. Utilizing data collection and clustering approaches can effectively regulate node energy in WSNs [7-8]. A well-known cluster-based routing technique called LEACH involves sensor nodes (non-CH) to collect data through their sensing area and send it to the CH [9]. Each cluster consists of a CH that collects, combines, and compresses CM data before transmitting them over a single hop to the BS or sink nodes. LEACH descendants have been proposed, including Centralized-LEACH, Improved-LEACH, Modified-LEACH, and Time-Based-LEACH [10-11]. This study aims to:

- Propose a novel optimized CH selection model.
- Introduce an improved DeepMaxout model to predict node energy and ensure energy efficiency while clustering.

- Evaluate the proposed model over traditional ones in order to showcase its effectiveness over the energy constraint.

II. LITERATURE REVIEW

Various studies have investigated different routing strategies for optimal CH selection. In [12], a dynamic CH selection method was proposed for WSNs. In [13], the LEACH method was proposed to reduce the randomness that clustering algorithms exhibit. In [14], a new Cluster Head Selection by Randomness with Data Recovery (CHSRDR) strategy was proposed to select a CH based on recovered data. In [15], the FLION clustering algorithm was proposed to create an energy-efficient routing scheme. In [16], a distributed CH selection strategy was presented to continuously optimize the energy use between sensors, considering the distances between the base station and the sensors. The reduction of energy consumption is one of the many issues that need to be resolved to improve WSN efficiency [17]. In [18], a novel application model for WSNs was proposed, in which raw data were collected through multi-hop networks, and a new HTC-RDC was presented to extend the lifespan of WSNs. In [19], the SLBR approach for heterogeneous cluster-based WSNs was investigated, which helps distribute the load between CHs. In [20], the DMOSC-MHRS method for the Internet of Drones environment was introduced, mainly aiming at selecting a CH with an optimal routing strategy. In summary, these studies emphasized the features and challenges of conventional WSN cluster-based routing strategies. This inspires the development of a new technique for optimal CH selection to prolong the overall lifetime of WSNs.

Essentially, WSN nodes depend on a limited battery power supply that can only keep them running for a certain period before they deplete. Improving the energy efficiency of every sensor node extends the WSN lifespan, and clustering is one of the best methods to achieve this. This study propose a novel WSN routing protocol to prolong the network lifespan and reduce energy consumption by calculating the optimal CH depending on its energy using the Firefly Algorithm. The suggested approach was compared with the EAMMH, BRE, NEAHC, SEP, E-SEP, LEACH, and WEB protocols. According to experimental data, the suggested strategy outperformed the comparable routing methods on energy usage and packet transmission between sensor nodes and base stations. The results clearly showed that the suggested approach could lengthen the WSN lifetime.

III. THE PROPOSED ARCHITECTURE OF CLUSTER-BASED ROUTING IN WSN

Since sensor nodes are small and self-sufficient devices with limited power, routing algorithms are crucial to improve network lifetime and energy consumption. Movement and data reception, collection, and analysis are only a few of the factors that cause nodes to consume their energy. This study introduced a cluster-based routing via CIOO that combined Osprey-Chimp optimization. Consider the WSN scenario simulated with nodes namely, normal node (N), intermediate node (I) and advanced node (A). In the initial stage, the energy of the nodes is predicted by an improved DeepMaxout model. Clustering takes place using the k-means clustering algorithm. For every cluster, CH selection is performed by the CIOO algorithm (Osprey and Chimp Optimization) considering energy prediction, inter- and intra-cluster distances, delay, and risk. Subsequently, routing is carried out using the CIOO algorithm considering improved trust and link quality.

A. *Node Energy Prediction using the Improved DeepMaxout Model*

The energy of a sensor node is the main factor in data transmission from a source to a destination node. However, it also depends on the distance they are from each other. According to the proposed model, an improved DeepMaxout was used to predict the energy of the nodes. Lets consider three types of nodes: Normal node (N), Intermediate node (I), and Advanced node (A). Energy consumption differs depending on the type of node. In the DeepMaxout model, node location, distance, and type are considered as input features, and then the target will be 0, 1, and 2. Thus, the node energy is predicted under three conditions, as shown in Table I. If the type of the node is normal, then the target value is fixed to 0 and its energy prediction value will be 0.5. Similarly, if the type of node is intermediate, its target value is 1 and its energy prediction will be 0.8. If the type of node is advanced, the target value is 2 and its energy prediction will be 1.

TABLE I. ENERGY PREDICTION OUTCOME

Node Type	Target	Energy (E)
N	0	0.5
I	1	0.8
A	2	1

B. *Improved DeepMaxout Architecture*

The primary component of DMN's multi-layered structure makes it a form of adaptable activation factor. In this section, positive and negative terms are specified as a nonzero slope through an effective activation function known as Maxout [21]. In general, Maxout supports measures to tackle the optimization challenge by partially defending the hidden elements from transitioning to an abnormal mode. While acting as an adaptable activation variable, Maxout does not work as a random function approximator. Improved DeepMaxout considers input features, such as node location, type, and distance, using an improved activation function to obtain a more accurate energy prediction. The activation function was determined as a hybrid form, tanh(*Swish*+*Softplus*), by combining two activation functions. Swish [22] is the smooth, non-monotonic function represented by:

$$f(x) = x \cdot Std(x) \tag{1}$$

where *Std*(*x*) represents the sigmoid function that is mathematically calculated by:

$$Std(x) = \left(1 + e^{(-x)}\right)^{-1} \tag{2}$$

The *Swish*'s characteristics are comparable to those of *Softplus*, a smooth function that is absolutely beneficial and continuous and is often considered a refined form of ReLU. The *Softplus* activation function [22] is expressed by:

$$f(x) = log\left(1 + e^{(x)}\right) \tag{3}$$

By adding (1) and (3), the combination of the two activation functions is obtained as:

$$(Swish + Softplus) = x \cdot Std(x) + log\left(1 + e^{(x)}\right)$$

$$(f(x) + f(x)) = x \cdot \left(1 + e^{(-x)}\right)^{-1} + log\left(1 + e^{(x)}\right)$$

$$2f(x) = \frac{x}{\left(1+e^{(-x)}\right)} + log\left(1 + e^{(x)}\right)$$

$$2f(x) = \frac{x+log\left(1+e^{(x)}\right)\times\left(1+e^{(-x)}\right)}{\left(1+e^{(-x)}\right)}$$

$$f(x) = \frac{\left[\frac{x+log\left(1+e^{(x)}\right)*\left(1+e^{(-x)}\right)}{\left(1+e^{(-x)}\right)}\right]}{2} \quad (4)$$

Usually, the hyperbolic tangent function [23] is used in the DeepMaxout model, which is a smoothened and zero-centered function, and the tanh function result is calculated by:

$$f(x) = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}} \quad (5)$$

This study employed a hybrid combination of tanh*(Swish + Softplus)* activation function in the improved DeepMaxout structure, expressed as:

$$\tanh(Swish + Softplus) =$$

$$\left\{\frac{\left[\frac{e^{x}-e^{-x}}{e^{x}+e^{-x}}\right]\left[\frac{x+log\left(1+e^{(x)}\right)\times\left(1+e^{(-x)}\right)}{\left(1+e^{(-x)}\right)}\right]}{2}\right\} \quad (6)$$

The outcome of the improved DeepMaxout model is the predicted energy value mentioned in Table I. After energy node prediction, all nodes are split into small divisions called clusters. In this study, the clustering process was carried out through the k-means clustering algorithm.

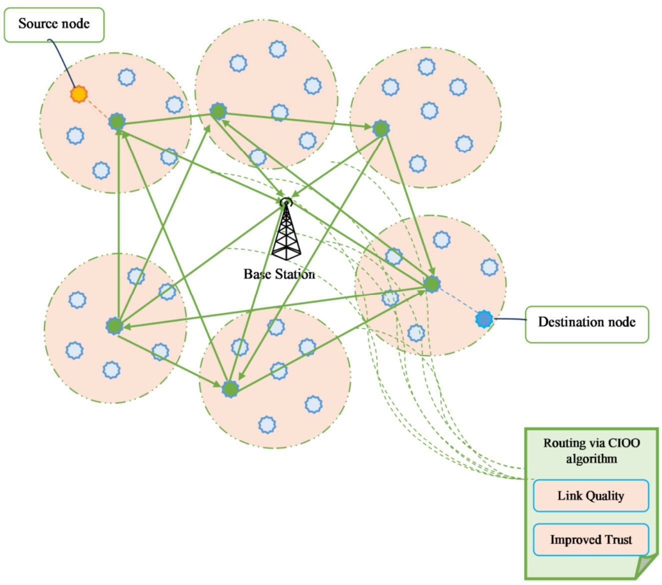

Fig. 1. The routing architecture using the CIOO algorithm.

C. Routing via CIOO Algorithm

After selecting the CH based on the proposed CIOO algorithm under various constraints, the routing is carried out via the same CIOO algorithm considering link quality and a newly evaluated trust. Figure 1 shows the architecture for routing via the CIOO algorithm.

1) Link Quality (LQ_R)

Link Quality (LQ_R) is one of the typical restrictions in the best possible routing and shows the quality of data packets that the destination has received. Equation (7) illustrates the way to calculate it in WSN. The ratio of the number of received to the sent packets is termed LQ_R.

$$(LQ_R) = \frac{P_r}{P_t} \quad (7)$$

where P_r denotes the number of packets received and P_t denotes the number of packets transmitted.

2) New Trust Evaluation

For every neighboring node (node that is within its transmission range), each node generates a trust degree value. This number represents the degree of trust in a neighbor. The trust degree value is generated using regional data, such as regional topological data, to ensure scalability. Let the level of trust between node P and neighbor Q at time t be denoted by $T_{P\text{-}Q}(t)$. The continuous range of 0 to 1 is the only range allowed for the trust degree value. A trust degree of 0 indicates total mistrust, while a value of 1 indicates complete trust. Trust [24] includes both direct and indirect trust. The final trust is formed by combining the values of indirect and direct trust.

Direct trust is determined by nodes interacting with each other. Distance and energy are evaluated as markers of trust according to:

$$DT_{(P-Q)} = \frac{Er}{d(node_P, node_Q)} \quad (8)$$

where $d(node_P, node_Q)$ indicates the differentiation distance between nodes P and Q, $DT_{(P\text{-}Q)}$ is the value of direct trust between P and Q, and E_r is the residual energy of node B. Indirect trust is based on a node's suggestion. The method for calculating indirect trust, which is added to the amount of trust value evaluated by the extra nodes, is given by:

$$IT_{(P-Q)} = \sum DT_{(P-R)} * DT_{(R-Q)} \quad (9)$$

where $DT_{(P\text{-}R)}$ denotes the direct trust calculated by P for R and $DT_{(R\text{-}Q)}$ denotes the value of direct trust determined by R for Q. Final trust is the sum of direct and indirect trust times the appropriate weight:

$$Trust_{(P-Q)}(T) = w * DT_{(P-Q)} + (1 - w) * IT_{(P-Q)} \quad (10)$$

In this case, the final trust computation uses W as 0.5. The proposed trust evaluation improves the trust value between nodes during routing. The packet delivery ratio is incorporated into the direct trust value to improve overall trust in routing. The following equation determines the improved direct trust value between nodes P and Q.

$$DT'_{(P-Q)} = PDR + \frac{Er}{d(node_P, node_Q)} \quad (11)$$

Packet Delivery Ratio (PDR*)* [25] is a metric that quantifies the proportion of total packets delivered to the total packets transmitted over a network between a source and a destination node. The intention is for the greatest number of data packets to arrive at the intended location. The network's performance increases with the value of *PDR*, which is calculated by:

$$PDR = \frac{DR}{(DR+DL)} \tag{12}$$

where *DR* denotes the data received, and *DL* denotes the data lost. Therefore, the final trust evaluation is expressed by:

$$ImprovedTrust_{(P-Q)}(T') = w * DT'_{(P-Q)} + (1-w) \times IT_{(P-Q)} \tag{13}$$

3) Objective Function for Routing

The routing objective function is defined as the minimum fitness function under the constraints of link quality and improved trust. Link quality and improved trust are calculated by (14) and (15):

$$Fit = min(w_5 * LQ_R + w_6 * T') \tag{14}$$

$$obj(f) = min(Fit) \tag{15}$$

where w_5 and w_6 denote the weight of link quality and improved trust, respectively. The summation of the total weight is represented as $\sum w_i = 1$.

4) Solution Encoding for Routing

The input given to the algorithm is the number of nodes. The population size is 10, the lower bound value is fixed to 1, and the upper bound value is *n*, which is the number of sensor nodes.

IV. RESULTS AND DISCUSSION

A simulation of the proposed cluster-based routing method in WSNs was carried out using MATLAB version R2023b on an Intel® Core™ i5-1035G1 CPU at 1.19 GHz with 20 GB total installed RAM, with 19.7 GB of it being usable. The performance analysis of the proposed CIOO and traditional approaches was estimated using many metrics. Figure 2 illustrates the network setup. The established network configuration parameters were *x* = 100 m and *y* = 100 m. The election probability of a node to become CH was 0.8, and the maximum number of rounds was 2000.

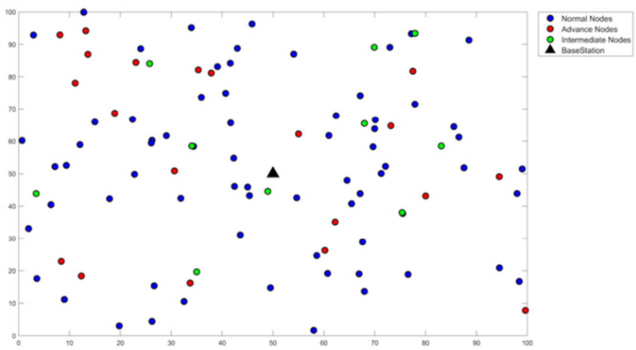

Fig. 2. Network setup.

A. Analysis of Residual Energy

Figure 3 shows the evaluation of residual energy in the CIOO and traditional schemes in the context of cluster-based routing in WSN. For a model to perform effectively, the residual energy must remain at a higher level. Initially, all algorithms achieved higher levels of residual energy, but as the number of rounds increased, the rate of residual energy began to decline. However, the CIOO method consistently maintained the highest residual energy, even in the final round. The CIOO approach achieved the highest residual energy in the 2000th round, exceeding the performance of PSO [26], DMOSC-MHRS [20], GOA [27], SMO [28], BOA [29], COA [30], and OOA [31]. Therefore, it can be assertively affirmed that the CIOO scheme in cluster-based routing for WSN not only excels in delivering remarkably efficient solutions but also maintains a notable level of energy efficiency.

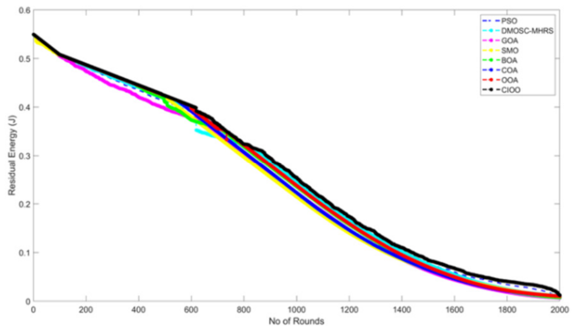

Fig. 3. Validation of residual energy.

B. Convergence Analysis

Figure 4 shows the convergence evaluation of the CIOO and PSO [26], DMOSC-MHRS [20], GOA [27], SMO [28], BOA [29], COA [30], and OOA [31] approaches for cluster-based routing in WSNs.

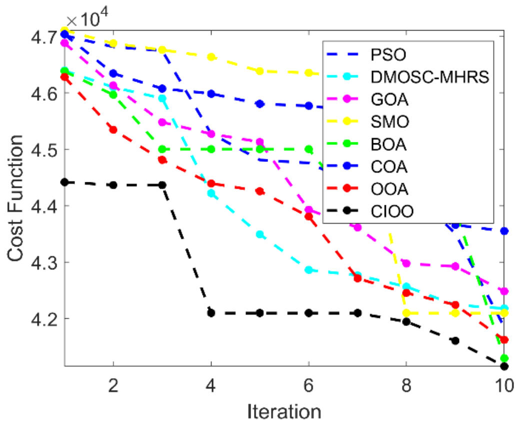

Fig. 4. Convergence analysis of CIOO and conventional methods.

The cost rate must be reduced for efficient cluster-based routing. Initially, the CIOO and conventional strategies exhibited higher cost values, but as the iterations progressed, there was a decrease in the cost rate. In particular, the CIOO scheme consistently achieved the lowest cost value from the initial to the final iterations. For the 10th iteration, CIOO yielded the lowest cost rate of 4.126×10^4, and the traditional approaches recorded the following cost rate values: PSO = 4.381×10^4, DMOSC-MHRS = 4.257×10^4, GOA = 4.294×10^4, SMO = 4.228×10^4, BOA = 4.139×10^4, COA = 4.375×10^4, and OOA = 4.198×10^4. We can see that the proposed method overperforms the conventional methods. The outstanding performance observed during the convergence evaluation highlights the CIOO's ability to achieve optimal cluster-based routing in WSNs.

C. Statistical Analysis on Residual Energy

Table II shows the statistical evaluation of CIOO and the conventional methods SMO [28], BOA [29], COA [30], and OOA [31] for cluster-based routing in WSNs. A metaheuristic technique was meticulously studied, and as a result, each method was subjected to hard evaluation to ensure remarkably exact estimates. To achieve this, a detailed evaluation was carried out inspecting critical statistical metrics. Together, these metrics provide a complete understanding of the efficiency and dependability of the approaches under investigation. The statistical analysis on residual energy showed that the CIOO recorded the highest residual energy rate under the maximum statistical metric, which was extremely higher than the SMO [28], BOA [29], COA [30], and OOA [31] approaches.

TABLE II. STATISTICAL ANALYSIS ON RESIDUAL ENERGY

Statistical Metrics	**CIOO**	**SMO [28]**	**BOA [29]**	**COA [30]**	**OOA [31]**
Minimum	0.012	0.011	0.008	0.010	0.010
Median	0.254	0.214	0.235	0.223	0.238
Standard Deviation	0.170	0.177	0.176	0.178	0.177
Maximum	0.550	0.550	0.549	0.550	0.550
Mean	0.258	0.239	0.245	0.243	0.248

V. CONCLUSION

This study suggested a new cluster-based routing algorithm for WSNs and simulated it in MATLAB R2023b. Initially, k-means clustering was used to cluster the sensor nodes. Then, the proposed algorithm was used to perform the optimal CH selection, primarily considering the energy constraint. The improved DeepMaxout model was used to forecast the node's energy consumption. The suggested CIOO method considers link quality and trust after selecting the CH when deciding on routing. Compared to conventional approaches, the proposed consistently maintained the highest residual energy, even in the final 2000th round. The statistical analysis and comparison showed that the proposed method exhibited the highest residual energy rate compared to the others. The proposed method should be further evaluated and compared with conventional methods in terms of energy consumption, journey duration, and security.

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