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ENERGY EFFICIENT CLUSTERING USING MODIFIED MONARCH BUTTERFLY FOR WIRELESS SENSOR NETWORK

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Abstract: Wireless Sensor Network (WSN) comprises a collection of sensor nodes deployed randomly in the sensing environment. Since energy efficiency remains a challenging design issue in WSN, clustering and routing techniques have emerged. The sensor nodes in WSN are restricted in energy, bandwidth and computation capabilities. In this research work, the WSN challenges, such as energy-constrained characteristics of the WSN sensor nodes, are focussed and can be resolved by using routing techniques. This paper presents an energy-efficient clustering with a modified monarch butterfly optimization-based multipath routing protocol (CL-BO-MRP) technique for WSN. The proposed model initially involves the cluster construction and Cluster Head (CH) selection process using Fuzzy Logic (FL). In addition, the Modified Monarchy Butterfly Optimization (MMBO) algorithm-based optimal route selection process determines the possible routes to a destination. The MMBO-based routing algorithm aims to reduce intra-cluster and inter-cluster communication costs. Applying fuzzy-based clustering and MMBO based routing helps achieve energy efficiency. An extensive simulation analysis is carried out to verify the adequate performance of the proposed models. The outcomes of the proposed models are examined under several aspects, such as Packet Delivery Ratio, Average delay analysis, Energy Consumption and Throughput. The detailed simulation outcome indicated the superiority of the proposed model CL-MMBO-MRP over the existing models under several aspects.

Keywords: Clustering, routing, optimization, fuzzy, delay, energy consumption, fitness, monarch butterfly, Wireless Sensor Network, Networks.

Introduction

A wireless sensor network (WSN) is a set of autonomous nodes or sensors that monitors the physical environment and records data. The sensed data may be sound, light, humidity, temperature, velocity, etc., gathered from the sensors and are collected, aggregated, and sent to the centralized node for processing [1, 2]. WSN plays a prominent role in various fields and real-time applications like forest fire, medical applications, military etc. Further research is being carried out in this field, extending to multipurpose smart applications. Energy consumption is one of the foremost essential aspects that have to be addressed in WSN. The network's lifetime should be enhanced to ensure all the nodes are working longer. Lifetime depends on the battery life, and the lifetime can be improved by efficient use of power [3].

Changing the battery is not always feasible due to the deployed location of the WSN. The intrinsic characteristics of each sensor node present extra communication protocol difficulties, particularly in terms of energy usage [4]. Applications for WSNs and their communication protocols are designed to be very energy-efficient. Limited power sources are carried by sensor nodes, generally powered by batteries that need to be replaced or refilled (for example, using solar power) when they run out of power. Some nodes will be deleted after their energy supply runs out since neither choice suits them [5]. Whether or not the battery can be recharged considerably influences the energy-saving approach. Therefore, although WSN protocols primarily focus on power saving, conventional networks are designed to increase performance measures like throughput and latency [6, 7].

WSN has versatile applications in various fields [8]. There are numerous issues associated with the performance of the WSN [9, 10]. The performance of sensor networks depends on the sensor nodes' behaviour in the location in which they are deployed. The integrity of the sensor nodes is crucial for improving the network's ability [11]. Clustering techniques in WSN form various sensor nodes into groups and select the CH. An adequate amount of research has been done regarding clustering in WSN [12]. Along with clustering techniques, the routing protocol design also plays a vital role in the performance of WSNs. This paper discusses some of the powerful clustering techniques, routing protocols, and the prime issues involved in WSN [13, 14].

Motivation

The arrival of modern technologies and innovations in real-time sensor-based applications need a solution for unmanned sensors. Many parameters related to the environments are unpredictable, and hence significant challenges motivate this research work. The main idea of the research work explains the need for energy and enhancing the network lifetime. Irrespective of the applications, energy conservation, scalability, and robustness are needed to withstand the stability of the network.

Research Objective

WSNs are primarily placed in remote location where battery resource is non-rechargeable. For the effective collection of data, all the sensor nodes have to be communicated effectively by addressing the issues like power limitation, node deployment cost, routing cost, and localization of nodes. Considering these general issues, the main objectives of the research work are listed.

- The cluster construction and Cluster Head (CH) selection process uses Fuzzy Logic (FL).
- Modified Monarchy Butterfly Optimization (MMBO) algorithm-based optimal route selection process takes place to determine the possible routes to a destination.
- The MMBO-based routing algorithm primarily intends to minimize intra-cluster and inter-cluster communication costs.

The research work is organized as follows: the overview of WSN, issues, motivation, and the research objective is detailed in Section 1; the recent research work in the WSN is discussed with the research gap in Section 2; the clustering process and the routing process using fuzzy assisted energy efficient clustering with modified monarch butterfly optimization based multipath routing protocol (CL-BO-MRP) technique is described in Section 3, the simulation analysis and the illustration is detailed in Section 4, the article is concluded with future research direction in Section 5.

Related Works

Sreedharan, P. S., & Pete, D. J. (2020) [15] studied WSN, which uses energy-efficient hierarchical clustering to improve the network lifetime. Changing CHs rotationally is done with their sensor nodes' degree. During the CH replacement time, the member node near the current CH will act as a temporary CH and handle the transition period's data transmission. By this method, redundancy can be avoided.

Wang et al. (2020) [16] proposed an essential factor in selecting the optimal CHs. An Improved Ant Colony Optimization(IACO) algorithm does this clustering process. The CH is determined using fuzzy C means considering cluster location, density, and other factors followed by the routing method. IACO introduces a polling mechanism in intra-cluster communication based on nodes' busy/idle nature. As optimization is done on both clustering and routing, it shows significant improvement in energy conservation.

Yang et al. (2021) [17] analyzed the sensor nodes placed in a harsh environment with inferior network connections for real-time data collection. The authors proposed a layer-based heterogeneous cluster routing algorithm. In this algorithm, nodes are divided into advanced and standard nodes. Advanced nodes have more power than others and are selected as CH, which aids in forming the network layers. Heterogeneous clustering is done across the layers, improving performance and energy efficiency.

Kandris, D., et al (2020) [18] presented a method for increasing the coverage and maintenance of the connectivity in WSN. The author proposed a novel approach to represent three-dimensional locations to improve range and maintain the connection. A distributed particle swarm optimization algorithm and a newly proposed three-dimensional virtual force algorithm are combined to maximize the sensor nodes' communication range.

Shafiq, M., et al. (2020) [19] proposed a Chaotic algorithm that selects the best CH to find the optimal routing path. The chaotic algorithm uses a fitness function based on energy consumption and load balancing among the nodes. Also, the algorithm takes care of cluster maintenance. Adaptive round time is also proposed in the cluster routing protocol, where results showed improvement compared with traditional methods.

The communication performance is enhanced concerning packet delivery ratio Nisha & Basha (2020) [20] and proposed a triangular fuzzy-based spectral cluster routing (TF-SCR). The cost of communication is calculated, and the authors' ultimate goal was to improve the network's reliability. Network reliability specifies the probability of the operational nodes in the network. The network's total nodes are connected in a tree structure based on the edge technique's weight. If there is no connection between any two nodes (direct or indirect way), it is considered unreliable. The penalty is added to the weight for all unreliable connections in the network.

Security is a critical aspect that must be taken care of. Several techniques are available to avoid attacks and detect malicious nodes. Clustering methods can be utilized to enrich the security of WSNs. Arjunan & Pothula (2019) [21] evaluated each node's process to see malicious nodes and avoid them becoming CH. Trust level system of nodes in WSN is calculated based on a node's characteristics in the cluster. Periodic authentication between CH and members is done to ensure authentication. Data encryption is done before transferring, which can be opened by an authentication key. Each node is verified based on its authentication key and data among CH and members. The optimal cluster head selection for energy efficient wireless sensor network using hybrid competitive swarm optimization and harmony search algorithm (HCSO-HAS) is developed to enhance the clustering process [22].

Many research works are discussed in the literature; the drawbacks identified are cluster member selection is complicated, and the routing also consumes much energy. The optimization fails due to early convergence, exploration, and exploitation ability. Considering the drawbacks, the cluster member selection is attained using fuzzy logic and the routing is accomplished using MMBO. The energy efficiency and the routing process are discussed in the subsequent sections.

Proposed Methodology

A WSN integrates a wireless network with autonomous low-cost sensors. The sensors are commonly employed to observe the physical parameters of the target environment. It finds useful for several application areas, namely environmental monitoring, forest fire detection, border management, etc. The sensor nodes comprise four significant units: sensing, processing, storing, and communicating. Using inbuilt batteries for sensor operation rapidly leads to the depletion of energy. In addition, the utilization of available energy in a proficient way is also an essential requirement in designing WSNs. To achieve energy efficiency in WSN, clustering and routing are considered powerful techniques. Firstly, clustering is constructing clusters by the effective choice of Cluster Heads (CHs) and Cluster Members (CMs). The role of CH is to gather data from the CMs and transmit it to the Base Station (BS) via single or multihop data transmission. The process of selecting the CHs plays a vital role in WSN. In addition, routing is choosing an optimal set of paths from source to destination. Generally, two types of communication exist in WSN: inter-cluster and intra-cluster communication. In most cases, the routing techniques are utilized for inter-cluster communication to determine the shortest routes from CHs to BS. Clustering and routing processes are considered the optimization problem and can be resolved using metaheuristic algorithms.

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The sensor nodes are arbitrarily placed in the target region and are initialized to perform the clustering process. Next, the clustering process gets executed to elect CHs using FL and construct clusters. The MMBO technique determines an optimal set of routes to a destination. At last, data will be transmitted from CHs to BS via inter-cluster communication.

Clustering Process

During the cluster construction process, the CHs are selected using FL. The presented model utilizes energy and distance as the input variable and fuzzy cost as the output variable. The fuzzy cost determines the Euclidean distance and the remaining energy. When the node with the least fuzzy cost exists in the coverage area, the node broadcasts it as the present CHs, and the nearby nodes join the cluster.

$$F_k = d(k,q)^{\alpha}/E_k \text{--------------(1)}$$

Where F_k is the fuzzy cost of node k, d (k,q) is the Euclidean distance, and q is the earlier CH of the cluster. E_k is the remaining energy of node k, and α is a constant denoting the cluster distribution.

Consequently, the CHs are chosen by

$$CH_x = \{p: F_p = \min(F_k)\,, k \in cluster_x\} \text{--------------(2)}$$

Where CH_x is the chosen CH of the $cluster_x$. is the Fuzzy cost of node p determined using Equation (3), min() designates the 'minimum of' operation. The chosen CH will signal that the election outcome is provided to all the nearby nodes. When the node receives the broadcast signal, it turns on the transmitting end and sends the data with the required transmission power as soon as the CH's broadcast signal intensity is reached. When a node receives numerous broadcasting signals, it sends the data to the CH with the strongest broadcast signal. The CHs use the TDMA mechanism to receive data from the node, eliminating packet loss and collision and lowering energy consumption.

Fuzzy logic is a mathematical framework for handling uncertainty and imprecision in decision-making. It can be applied to cluster head selection. The cluster head selection process involves evaluating specific criteria or attributes and assigning a degree of membership to each potential cluster head candidate. Fuzzy logic allows us to quantify the membership degree based on the requirements, which helps make a more informed decision. Different factors or attributes relevant to cluster head selection are considered: energy level, distance to the base station, and connectivity. IF the energy level is high AND the distance to the base station is low, THEN membership degree as a cluster head is very high.

The input criteria are evaluated, and the membership degree is calculated for each selected candidate as a cluster head based on the fuzzy rules. This can involve applying fuzzy logic operators (e.g., AND, OR, NOT) and membership functions to determine the degree of membership for each criterion. Combine the membership degrees from different standards using aggregation operators (e.g., MAX, SUM, AVG) to obtain an overall membership degree for each candidate. The defuzzification method is applied to obtain a crisp value from the aggregated membership degrees. The candidate with the highest crisp value is selected as the cluster head.

Routing Process

A multi-objective minimization problem is what the multi-hop routing procedure is thought to be. Reducing the cost of intra-cluster and inter-cluster communication is the primary goal. The MMBO algorithm is used to choose the best routes to a location. Equations 3 and 4 are used to optimize the communication cost.

$$\sum_{k=1}^{|V|} \sum_{m=1}^{|C_k|} W_{cm_{m,k} \rightarrow CH_k} \text{--------------(3)}$$

$$\sum_{k=1}^{|V|} W_{CH_k \rightarrow NextHop_{CH_k}} \text{--------------(4)}$$

where, $CH_k \rightarrow$ CH number k; k $\rightarrow$ has chosen CH count; $NextHop_{CH_k} \rightarrow$ Next hop for CH_k; $cm_{m,k} \rightarrow$ CM count m of cluster k; V $\rightarrow$ vector including the chosen CHs; The vector covering the CMs in the cluster refers to CH_k.

The MMBO algorithm is a well-known algorithm based on the nature of a particular species group with a collective behaviour, such as bees, butterflies, etc. It falls under the category of swarm intelligence approaches. Wang et al. developed the MMBO algorithm based on the cunning behaviour of butterflies that originated in North America. The beauty of the colours orange and black may recognize it. The monarch butterfly migrates twice a year, much like other butterflies do. The original migration starts in Canada and goes to Mexico; the subsequent migration returns to the beginning. Several optimization problems are solved by drawing inspiration from the butterfly's migrational behaviour. To arrive at the best answer to the problem, a specific set of guidelines and essential concepts are followed.

Each butterfly creates a population in either land_1 (the location before migration) or land_2 (the location after migration). Regardless of whether the parents were present in land_1 or land_1 & 2, the migration operator creates each unique butterfly child. A fitness function excludes the kid or the parent from the population while keeping the sample intact. The fitness function, passed down to the next generation and stayed the same across the migration operator, determines which butterflies are selected. The butterfly starts to migrate during the first few days of April, and the reverse migration begins in September. The NP is represented by the monarch butterfly count in the two lands and indicates the whole population. The butterfly's migratory process may be described as follows:

$$X_{i,k}^{t+1} = X_{r1,k}^{t} \text{--------------(5)}$$

where $X_{i,k}^{t+1}$ signifies the Kth element of X_i at t+1 round expressing the position of the butterfly i, and $X_{r1,k}^{t}$ represent the Kth element of the recent generation position. At this point, r is an arbitrary number determined as follows.

$$R = rand \times peri \text{--------------(6)}$$

Where peri denotes the migration duration, at the same time, in case r>p, then the Kth element of the current generation position are defined as follows:

$$X_{i,k}^{t+1} = X_{r2,k}^{t} \text{--------------(7)}$$

where $X_{r2,k}^{t}$ Characterizes the Kth element of X_{r2} at t round of butterfly r2, and P defines the ratio of monarch butterflies in land_1. By modifying the value of P, a tradeoff in the direction of migration between two lands 1 and 2 occurs. When the P value is high, it indicates that the butterflies are chosen from land_1 and vice versa. The position of the butterflies gets modified when the created rand $\leq P$. The updated location of the butterflies can be determined as follows.

$$X_{j,k}^{t+1} = X_{best.k}^{t} \text{--------------(8)}$$

where $X_{j,k}^{t+1}$ defines the Kth element of X_j at t+1 round, denoting the butterfly jth position, and $X_{best.k}^{t}$ Defines the Kth element of X_{best} at the present round t in land_1 and land_2. In case rand>P, it gets updated using Equation (9):

$$X_{j,k}^{t+1} = X_{r3.k}^{t} \text{--------------(9)}$$

At the same time, in the case of rand>BAR, the new location is updated using Equation (10)

$$X_{j,k}^{t+1} = X_{j,k}^{t+1} + \alpha(dx_k - 0.5) \text{ --------------(10)}$$

where BAR defines the adjustment rate of the butterfly and dx is the walk step of jth butterfly, which is determined by carrying out the Lévy flight operation as given below:

$$dx = Levy(X_j^t) \text{ --------------(11)}$$

α in Equation (12) denotes a weighted factor which is estimated as follows:

$$\alpha = S_{max}/t^2 \text{--------------(12)}$$

where S_{max} Defines the length of the butterfly walk in one step, and t denotes the current round.

Result and Discussion

This section explains the simulation setup and the simulation analysis of the research work in this article. Setting up a Wireless Sensor Network (WSN) simulation involves creating a virtual environment that emulates the behaviour and characteristics of a real-world WSN. Simulations allow researchers and developers to analyze and evaluate various aspects of the network's performance, such as throughput, average delay, energy consumption, and packet delivery ratio. The research uses NS-2 simulation with 500 nodes, whereas the nodes are placed arbitrarily. The simulation arrangement is specified in Table 1.

Table 1. Description if Simulation

Parameters	**Value**	**Symbol**
Network Region	500×500	Row×Column
Clusters	Differs	CH
Number of Nodes	50~100	N
Initial Weight	0.42	W_i
Energy	100Joules	E_{node}

***Throughput**:* Throughput in a Wireless Sensor Network (WSN) refers to the amount of data that can be transmitted successfully over the network within a given time period. It is a measure of the network's capacity to transfer data effectively. The throughput calculation in a Wireless Sensor Network (WSN) involves considering the data rate and efficiency of the network. The basic formula for calculating throughput is as follows:

$$Throughput = \frac{Total\ Data\ Transmitted}{Total\ Time\ Taken} \text{--------------(13)}$$

The throughput comparison for different numbers of nodes and existing systems is given in Table 2 and illustrated in Figure 1.

Table 2. Comparison of Throughput

Number of Nodes	IACO	HCSO-HSA	TF-SCR	CL-MMBO
100	567	584	613	645
200	623	634	654	675
300	685	693	723	745
400	723	741	789	798
500	742	785	834	856

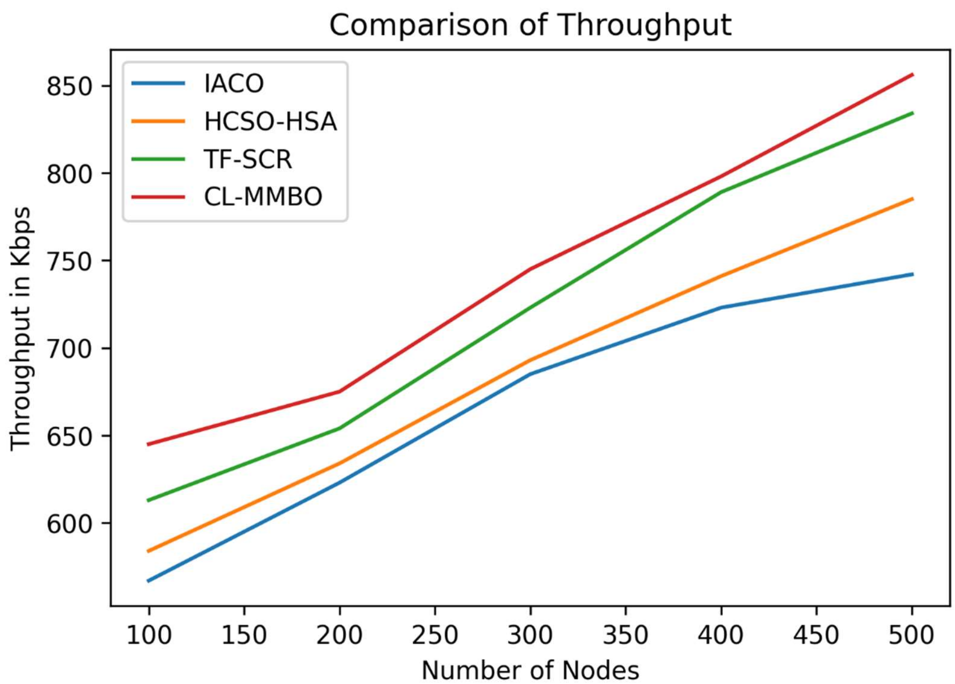

Figure 1. Comparison of Throughput

Figure 1 depicts the comparison of throughput for the existing techniques, namely IACO [16], HCSO-HAS [20], TF-SCR [22], and proposed CL-MMBO. The proposed approach is compared for nodes 100, 200, 300, 400, and 500. The proposed method attains 645, 675, 745, 798, and 856 kbps throughput for the nodes 100, 200, 300, 400, and 500, respectively. The acquired throughput is higher when compared to other techniques, where the highest throughput identifies effective data delivery.

Average Delay*:* The average delay in a Wireless Sensor Network (WSN) refers to the average time it takes for a data packet to traverse the network from the source node to the destination node. It is a measure of the latency or delay experienced in the network. The average delay is calculated as follows:

$$Average\ Delay = \frac{Sum\ of\ Delay\ at\ Each\ Stage}{Total\ Number\ of\ Packets} \text{--------------}(14)$$

The average delay comparison for different numbers of nodes and existing systems is given in Table 3 and illustrated in Figure 2.

Table 2. Comparison of average delay

Number of Nodes	IACO	HCSO-HSA	TF-SCR	CL-MMBO
100	345	323	314	278
200	356	334	322	291
300	385	365	351	301
400	390	378	361	312

500	425	419	391	332

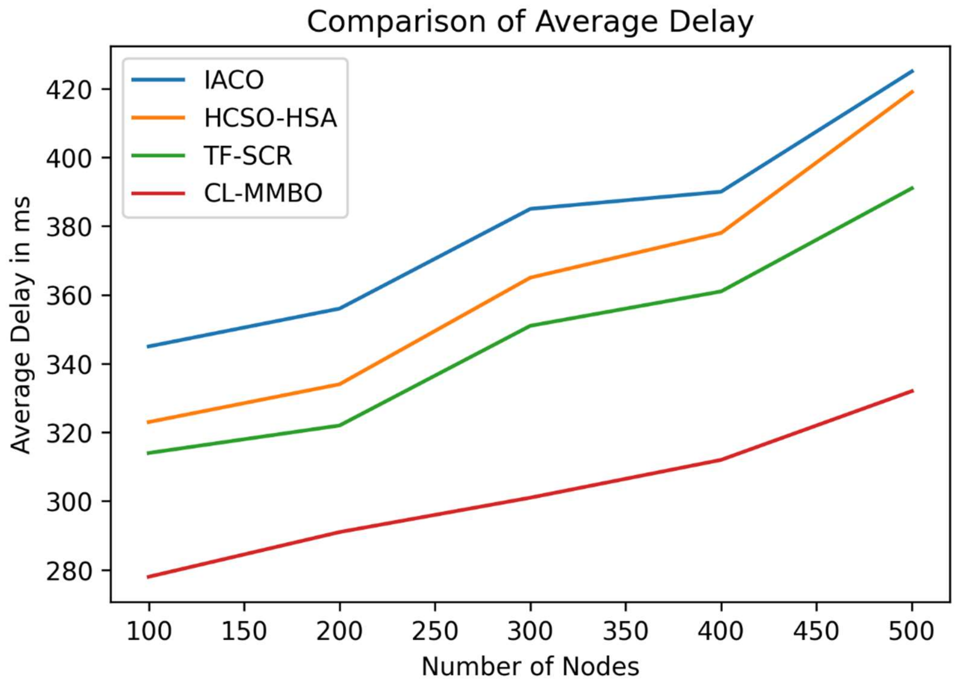

Figure 2. Comparison of average delay

Figure 2 compares the average delay for the existing techniques, namely IACO, HCSO-HAS, TF-SCR, and proposed CL-MMBO. The proposed approach is compared for nodes 100, 200, 300, 400, and 500. The proposed method attains 278, 291, 301, 312, and 332 ms average delay for the nodes 100, 200, 300, 400, and 500, respectively. The acquired average delay is minimal compared to other techniques, where the minimal average delay identifies effective data delivery.

Energy consumption*:* Energy consumption in a Wireless Sensor Network (WSN) is crucial due to the limited energy resources available to sensor nodes. Various approaches can be used to estimate the energy consumption in a WSN, including empirical measurements, analytical models, and simulation-based studies. Energy consumption can be quantified in joules, millijoules, or as an average power consumption rate in watts. Efficient energy management techniques in WSNs aim to optimize energy consumption, prolong the network's lifetime, and enhance the overall network performance. Calculating the energy consumption in a Wireless Sensor Network (WSN) involves considering the energy consumed during sensing, processing, communication, idle listening, and sleep modes. Here's a breakdown of the formula for estimating energy consumption in a WSN:

$$Energy\ Consumption = \left(Energy_{sensing} + Energy_{processing}\right) + (Energy_{communication}) + (Energy_{idle} + Energy_{sleep}) \text{ --------------(15)}$$

The energy consumption comparison for different nodes and existing systems is given in Table 4 and illustrated in Figure 3.

Table 4. Comparison of energy consumption

Number of Nodes	IACO	HCSO-HSA	TF-SCR	CL-MMBO
100	0.567	0.518	0.503	0.421
200	0.612	0.520	0.549	0.458
300	0.651	0.572	0.597	0.478
400	0.698	0.651	0.691	0.551
500	0.721	0.731	0.789	0.581

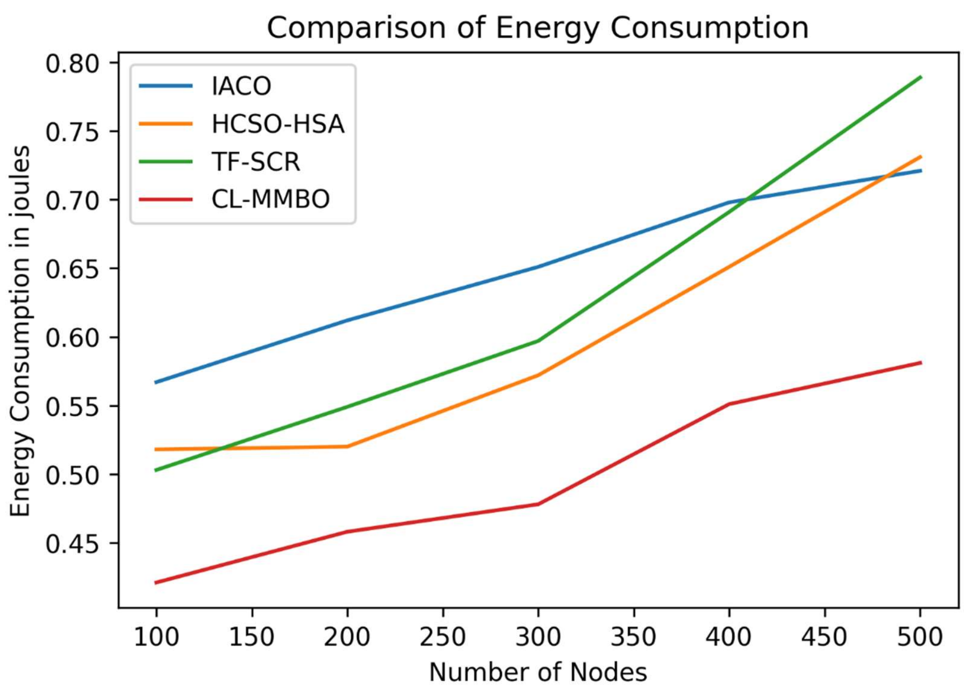

Figure 3. Comparison of energy consumption

Figure 3 depicts the comparison of energy consumption for the existing techniques, namely IACO, HCSO-HAS, TF-SCR, and proposed CL-MMBO. The proposed approach is compared for nodes 100, 200, 300, 400, and 500. The proposed method attains 0.421, 0.458, 0.478, 0.551, and 0.581j energy consumption for the nodes 100, 200, 300, 400, and 500, respectively. The acquired energy consumption is minimal compared to other techniques, where the minimal energy consumption identifies effective data delivery.

Packet Delivery Ratio (PDR): PDR in a Wireless Sensor Network (WSN) is a metric used to evaluate the reliability and effectiveness of data transmission within the network. It represents the ratio of successfully received packets to the total number of packets sent by a source node. The formula for calculating the PDR in a WSN is as follows:

$$PDR = \frac{Successfully\ Received\ Packet\ Count}{Successfully\ Sent\ Packet\ Count} \text{--------------}(16)$$

The PDR comparison for different numbers of nodes and existing systems is given in Table 5 and illustrated in Figure 4.

Table 3. Comparison of PDR

Number of Nodes	IACO	HCSO-HSA	TF-SCR	CL-MMBO
100	81	84	92	93
200	83	86	93	94
300	85	88	94	95
400	86	89	95	96
500	87	90	96	97

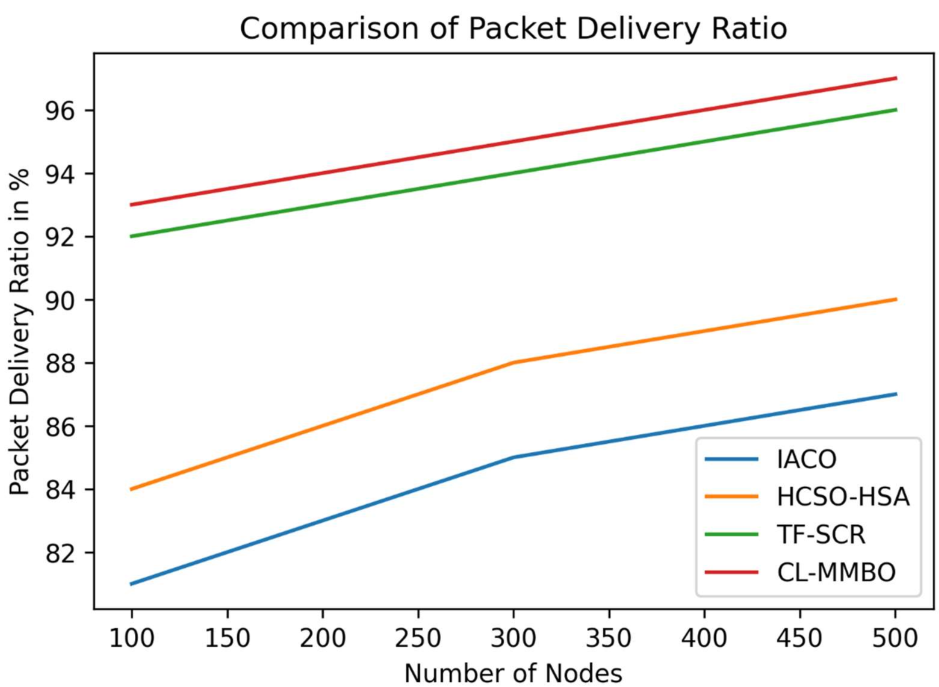

Figure 4. Comparison of PDR

Figure 4 depicts the comparison of PDR for the existing techniques, namely IACO, HCSO-HAS, TF-SCR, and proposed CL-MMBO. The proposed approach is compared for nodes 100, 200, 300, 400, and 500. The proposed method attains 93, 94, 95, 96, and 97% PDR for the nodes 100, 200, 300, 400, and 500, respectively. The acquired PDR is minimal compared to other techniques, where the highest PDR identifies effective data delivery. For 500 nodes, the PDR is 10%, 7%, and 1% higher than the approaches IACO, HCSO-HAS, and TF-SCR.

Conclusion and Future Work

This study uses a brand-new CL-MMBO approach to improve WSN energy efficiency. The sensor nodes are initially initialized and positioned arbitrarily in the target region to accomplish the clustering process. The clustering procedure is then carried out to create clusters and choose CHs based on FL. The CL-MMBO approach is then used to select the best possible collection of routes to the target. The cost of intra-cluster and inter-cluster communication is to be decreased by the CL-MMBO-based routing method. Inter-cluster communication will finally be used to transfer data from CHs to BS. To confirm that the performance metrics of the given models are effective, a thorough simulation study is conducted. The models' current results are reviewed from several aspects, including throughput, average delay analysis, energy consumption, and packet delivery ratio. The results collected sufficiently demonstrated the provided model's significantly superior performance over the alternatives already in use.

To improve energy efficiency as much as possible, data aggregation models can be added to the proposed model as a part of future work that includes effective multipath routing. Additionally, a hybrid data transmission paradigm, in which data is transmitted in both proactive and reactive ways, can improve the routing performance protocol. Additionally, the maintenance stage may be used to increase the efficacy of the models that have been given. Cryptographic algorithms can help improve the security of the suggested methods. Deep learning models can also take the given methods to the next level.

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