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ANALYSIS AND IMPROVED METAHEURISTIC PROCEDURE FOR ROUTING IN WIRELESS SENSOR NETWORK

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Abstract

Wireless sensor networks, also known as WSNs, play a crucial role in a wide variety of applications, ranging from environmental monitoring to smart cities. In these applications, effective data routing is fundamental to the durability and dependability of the network. Routing in wireless sensor networks (WSNs) presents a number of significant issues due to the limited energy resources of sensor nodes, the dynamic nature of network topologies, and the requirement for communication that is both scalable and reliable. These issues can be addressed with the help of metaheuristic algorithms, which offer potential solutions by providing resilient and nearly optimum routing systems. This article provides an examination of various metaheuristic techniques that are currently in use, including Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Simulated Annealing (SA). The purpose of this research is to highlight the advantages and disadvantages of these techniques when applied to the context of wireless sensor network (WSN) routing. Additional to this, we present an improved metaheuristic technique that incorporates hybrid approaches, dynamic adaptation mechanisms, and multi-objective optimization in order to improve the flexibility and efficiency of routing. The results of the experiments show that the suggested method considerably enhances network lifetime, data delivery rates, and overall performance. As a result, it provides a reliable solution for contemporary wireless sensor network applications.

Keywords: *Metaheuristic, Routing, WSNs*

Introduction

Wireless sensor networks, also known as WSNs, have become an indispensable component in a wide range of applications, including environmental monitoring, healthcare, industrial automation, and smart cities technology. One type of wireless sensor network (WSN) is made up of geographically dispersed autonomous sensors that monitor the circumstances of the environment or the physical environment. These sensors work together to send their data over the network to a central point or sink. It is the routing protocol of a wireless sensor network (WSN) that is responsible for establishing the pathways that data packets take from source nodes to the sink. The efficacy of a WSN is substantially dependent on the routing protocol. For the purpose of extending the lifetime of the network and ensuring that data transmission is reliable, effective routing is of the utmost importance. This is because sensor nodes have limited energy resources, and network topologies are inherently dynamic.

Challenges in WSN Routing

Routing in WSNs presents several unique challenges:

Energy Efficiency: Sensor nodes are typically battery-powered, and replacing or recharging batteries is often impractical. Hence, energy-efficient routing protocols are crucial to extend the network's operational lifetime.

Scalability: WSNs can consist of a large number of nodes, making scalability an important factor. The routing protocol must handle increased network size without a significant degradation in performance.

Reliability: Data must be reliably transmitted even in the presence of node failures and varying network conditions.

Adaptability: The protocol must adapt to changing network topologies due to node mobility or environmental factors.

Metaheuristics in WSN Routing

When it comes to the difficult routing issues that are present in WSNs, metaheuristic algorithms provide some potential answers. The exploration of a broad solution space is what these algorithms do in order to give approximate answers to optimization issues. Because of their adaptability, flexibility, and capacity to provide near-optimal solutions within tolerable computing timescales, they are very useful for WSN routing. Due to these characteristics, they are particularly effective. Methods such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Simulated Annealing (SA) are examples of common metaheuristic techniques.

Genetic Algorithms (GA): GA uses operations inspired by natural evolution, such as selection, crossover, and mutation, to iteratively improve a population of solutions.

Particle Swarm Optimization (PSO): PSO mimics the social behavior of birds or fish to find optimal solutions by adjusting the trajectories of individual particles in the search space.

Ant Colony Optimization (ACO): ACO is inspired by the foraging behavior of ants and uses pheromone trails to guide the search for optimal paths.

Simulated Annealing (SA): SA is inspired by the annealing process in metallurgy and uses probabilistic jumps to escape local optima and converge to a global optimum.

Improved Metaheuristic Procedure for WSN Routing

In spite of the fact that classical metaheuristics have demonstrated their effectiveness in WSN routing, there is an ongoing requirement for advancement in order to meet the ever-evolving issues posed by WSNs. The integration of several metaheuristic methods and the refinement of algorithmic components in order to increase performance are both components of an enhanced metaheuristic technique for routeing wireless sensor networks (WSN). Among the most important components of this enhanced method are:

Hybrid Metaheuristics: Combining different metaheuristic approaches can leverage the strengths of each method while compensating for their weaknesses. For instance, a hybrid GA-PSO algorithm can utilize the global search capability of GA and the fast convergence of PSO.

Dynamic Adaptation: The algorithm should dynamically adapt to changing network conditions, such as node failures or energy depletion, to maintain optimal routing paths.

Multi-objective Optimization: Addressing multiple objectives simultaneously, such as minimizing energy consumption, maximizing data delivery rate, and balancing the load among nodes.

Efficient Initialization and Local Search: Enhancing the initialization process and incorporating efficient local search techniques can significantly improve the quality of solutions and the convergence speed.

System Model

In the first place, network models and the topological infrastructure that supports them are established as diverse network configurations are introduced in accordance with the requirements of applications. All of the characteristics of SNs are present in the network systems. On the other hand, the development of wireless sensor networks (WSNs) involves the usage of nodes from the sensing region in order to generate a topological infrastructure where the data is acquired. This occurs during the network infrastructure. For this reason, the protocol that is being provided makes the assumption that the later network models and infrastructure will be present.

Network assumptions:

1. The network is comprised of one base station (BS), a group of controllers (CH), and a group of switches (SNs).
2. The power for the BS was supplied from an outside source, whereas the energy needed for the SNs is limited.
3. It is presumed that once it is dead, it can be removed from the power source.
4. Each and every SN is identical

Network structure:

a. In the first place, every node is employed in an arbitrary manner from the sensing region.
b. Over the course of a network's existence, the location of the node does not change.
c. Within the core of the sensing areas was where the BS was situated.
d. There was an inability to set the count of clusters.
e. Along with their closest CH, all of the regular nodes, which are also referred to as leaf nodes, are present.

In the event that the topology of the network was established, the method for creating the entire network connection would begin, while the stage of setting up would be implemented. During the stage of setting up, choices were made to pick primary CHs for the purpose of constructing primary cluster network configurations. The provided technique makes the assumption that the future energy consumption method will be used throughout the process of selecting the optimal CHs.

Analysis of Different Cluster based Routing Techniques

A hybridization of meta-heuristic cluster based routing (HMBCR) technique is developed by Al-Otaibi et al. [11] for wireless sensor networks (WSN). The HMBCR system is essentially comprised of a brainstorm optimized with levy distribution (BSO-LD) based clustering technique. This procedure makes use of a fitness function (FF) that incorporates four factors, namely the distance to neighbors, energy, network load, and distance to BS. In addition, a routing model that was based on WWO-HC was created in order to provide the best possible selected route. Using Internet of Things (IoT)-supported wireless sensor networks (WSNs), Lakshmanna et al. [12] investigate an enhanced meta-heuristic-driven energy-aware CBR (IMD-EACBR) strategy. Obtaining the highest possible energy consumption and network longevity is the objective of the technique that has been provided. In order to do this, the strategy that was just described first proposes to implement an improved Archimedes optimization algorithm-based clustering (IAOAC) approach for CH selection (CHS) and cluster arrangement.

A Hybrid ABC and Monarchy Butterfly Optimization Algorithm (HABC-MBOA) that is based upon the CHS technique was proposed in [13] in order to be the most selective of CHs in the clustering operation. This HABCMBOA that has been offered replaces the use bee step of ABC with the modified butterfly modifying function of MBOA. This is done in order to avoid the prior trap of solutions as to the local optimal point and delayed convergence while maintaining the trade-off between exploitation and examination. This approach was provided as an anchor role in the process of eliminating the deficiency of the ABC technique with regard to the possibility for universal searching. In addition, this projected HABC-MBOA eliminates the possibility of CHs being overloaded with a maximum number of SNs, which is the result of the rapid death of SNs that occurs during the implementation of an inefficient CHS method.

For the purpose of finding an optimal CH from among the node groups, the Butterfly Optimization Algorithm (BOA) was utilized in publication [14]. It is possible to optimize the CHS by utilizing the nodes' RE, node centrality, the distance between the neighbor and the BS, aloofness to the BS, and the node mark. By utilizing ACO, it is possible to identify the path that leads from the BS to the CH. This is accomplished by selecting the most optimal path that takes into account the node gradation, distance, and RE. Grant a hybrid meta-heuristic algorithm related clustering including multihop routing (HMA-CMHR) protocol for wireless sensor networks (WSN) in research paper [15]. A number of processes, including data transmission, node initialization, clustering, and routing, are included in the method that has been presented. In the first step of the HMACMHR method, a quantum HSA (QHSA) related clustering process will be utilized in order to choose the most suitable CH subset. After that, the improved cuckoo search (ICS) technique's route-related method was utilized in order to obtain the most comprehensive collection of routes.

Mohan et al. [16] describe an improved metaheuristic-related clustering algorithm for underwater wireless sensor networks (WSNs) that includes a multihop routing protocol. This protocol is referred to as the IMCMR-UWSN method. The selection of CHs and the most effective pathways to destiny was the primary objective of the strategy that was described earlier. Two different processes are included in the IMCMR-UWSN strategy. Multi-hop routing that is aimed toward the self-adaptive glow worm swarm optimization method (SA-GSO) and clustering that is oriented toward the chaotic krill head algorithm (CKHA) are two examples. A number of factors, including inter-cluster distances, RE, and intra-cluster distances, will be taken into consideration when the CKHA approach is used to pick organizations and CHs. As an additional point of interest, the SA-GSO method will generate an FF that incorporates four factors, namely trust, RE, detachment, and delay.

Using BOA, the researchers in [17] study were able to select the most appropriate quantity of CH from among the nodes. The RE of the node, interspace from nodes, and interspace from the BS, as well as the degree of the node and the relevance of the node, were the variables that one might take into consideration while selecting the CH. The PSO may be utilized for the purpose of constructing the CH by selecting certain variables, such as interspace, from both the BS and the CH. You have the ability to choose the course via the ACO system. By maximizing the remaining power, interspace, and choose node degree, the route was optimized to its full potential.The model of metaheuristics cluster-related routing method for energy-efficient wireless sensor networks (MHCRTEEWSN) was the centre of attention for BARNWAL et al. [18]. Through the use of routing and clustering processes, the MHCRTEEWSN approach that has been suggested primarily concentrates on improving the energy efficiency and longevity of wireless sensor networks (WSN). Within the MHCRTEEWSN technique, the whale moth flame optimization (WMFO) methodology is utilized for the purpose of achieving a successful clustering operation. This approach is utilized for the FF linking balance factor, intra-cluster distance, and inter-cluster distance.

In [19], a multi-Objective nature-inspired approach that is important to the Shuffled frog-leaping algorithm and the Firefly Algorithm was modelled as an application-specific clustering-related multi-hop routing protocol. This technique was given the moniker MOSFA. The multi-objective operation of MOSFA takes into consideration a number of variables, including intra- and inter-cluster detachments, load of clusters, the relative importance of nodes, overlap, and distances from the sink, in order to select appropriate CHs for each one of the rounds. Moreover, an additional multi-objective function may be modeled for the purpose of selecting the forwarding nodes from the routing stage. For the purpose of attaining the optimal performance that is pertinent to the network demands in accordance with the specific application, the controlled variables of MOSFA in the cluster and multi-hop stages are properly set.

A clustering and routing strategy that is efficient in terms of energy consumption was developed in [20]. An ICSA that would make use of a novel multiobjective FF was modeled in order to achieve the highest possible CHS. In addition, the Monkey search algorithm was utilized in order to determine the most efficient line of communication between the CH and the sink nodes. Within the context of the Yellow Saddle Goatfish Algorithm (YSGA), new energy-efficient clustering routing methods for wireless sensor networks (WSNs) were suggested in [21]. TIT is a potential solution that might be considered for extending the lifespan of the network by lowering the amount of energy that is used. Within its clustering structures, the network will take into consideration both BS and CHs sets. The YSGA method allows for the determination of the number of CHs as well as the selection of the best CHs, provided that the SNs are assigned to the CH that is closest to them. YSGA has the ability to modify the cluster structure of the network in order to provide the most optimal distribution of CHs and to reduce the distance between any two points of communication.

The author of [22] presents a reactive hybrid protocol that makes use of the hybridization of ACO in conjunction with the PSO approach in order to ensure that the lifespan of the network is increased. Using a reactive data communication technology that can be implemented into the hybridization of PSO and ACO methodologies, the estimated RAP methodology will be used to improve energy efficiency. This technology will be used to communicate reactive data. The clusters may be systematized based on the RE at first, and then the RAP technique that was developed is carried out in order to improve the aggregation of data across clusters and reduce the amount of information that is sent between them simultaneously.As an efficient routing protocol for acquired wireless sensor networks (WSN), the authors of [23] modeled a fuzzy knowledge-related meta-heuristic algorithm that was connected to the multi-objective fuzzy inference system (moFIS) and bacterial foraging optimizations (BFOs). This approach was referred to as moFIS-BFO. In the method that has been provided, the moFIS may be utilized for the purpose of determining the probability that each node will become a CH in accordance with several criteria. These criteria include the detachment of BS, the degree difference, the total distance to neighbors, and the RE metrics. Through the usage of the BFO, appropriate CHs were selected for each round, taking into consideration the estimated odds of the nodes.

IoT-supported CBR protocol for data-centric wireless sensor networks (ICWSN) is developed by Vaiyapuri et al. [24], and it is referred to as CBRICWSN. A clustering technique that is linked to black widow optimization (BWO) would be used to the approach that was created in order to choose the best possible collection of CHs. Furthermore, the technique that was discussed earlier incorporates an oppositional ABC (OABC) related routing mechanism with the purpose of selecting pathways in the most efficient manner.A technique was developed in [25] that allows for the selection of the CH as well as the selection of the effective route in a WSN for Internet of Things bids. It is possible for the CHS to be a component of clustering that is carried out by means of a rider optimized algorithm (ROA) that assumes three objectives, including latency, energy, and distance. The routing was carried out by selecting the most effective and efficient routes through the application of the multi-objective sailfish optimization method (SFO).

Performance Validation

Several different cluster-based routing strategies are evaluated in this section for their performance efficiency. Table 1 and Figure 2 present the results of an analysis of the alive node (ALN) of various different cluster-based routing strategies [11-13]. Given these findings, it can be deduced that the currently available models have demonstrated higher ALN values in comparison to alternative approaches. As an illustration, the FUCHAR, GWO, HABC-MBOA-CHSS, FFCGWO-CHSS, and IMD-EACBR models have each acquired an ALN of 94, 96, 98, 93, and 99 correspondingly on a total of 250 rounds. As an additional point of interest, the FUCHAR, GWO, HABCMBOA-CHSS, FFCGWO-CHSS, and IMD-EACBR methods have each achieved an ALN of 88, 88, 89, 84, and 87 respectively on 500 rounds. As an additional point of interest, the FUCHAR, GWO, HABC-MBOA-CHSS, FFCGWO-CHSS, and IMD-EACBR methods have achieved an ALN of 80, 87, 87, 78, and 79 correspondingly on 750 rounds. In addition to this, during the course of one thousand rounds, the FUCHAR, GWO, HABC-MBOA-CHSS, FFCGWO-CHSS, and IMD-EACBR approaches have achieved an ALN of 75, 82, 82, 73, and 70, respectively. Following a total of 1250 cycles, the FUCHAR, GWO, HABC-MBOA-CHSS, FFCGWO-CHSS, and IMD-EACBR systems have finally achieved an ALN of 65, 78, 73, 74, and 63, respectively.

Table 1 The ALN study of a number of different cluster-based routing algorithms subjected to a different count of rounds

Alive Nodes(%)					
No. of Rounds	FUCHAR	GWO	HABC-MBOA-CHSS	FFCGWO-CHSS	IMD-EACBR
0	100	100	100	100	100
250	94	96	98	93	99
500	88	88	89	84	87
750	80	87	87	78	79
1000	75	82	82	73	70

1250	65	78	73	74	63
1500	60	65	61	51	57
1750	51	59	60	0	53
2000	46	42	0	0	45
2250	32	30	0	0	40
2500	30	20	0	0	29
2750	19	16	0	0	10
3000	10	12	0	0	6
3250	0	8	0	0	4
3500	0	0	0	0	2
3750	0	0	0	0	0
4000	0	0	0	0	0
4250	0	0	0	0	0
4500	0	0	0	0	0

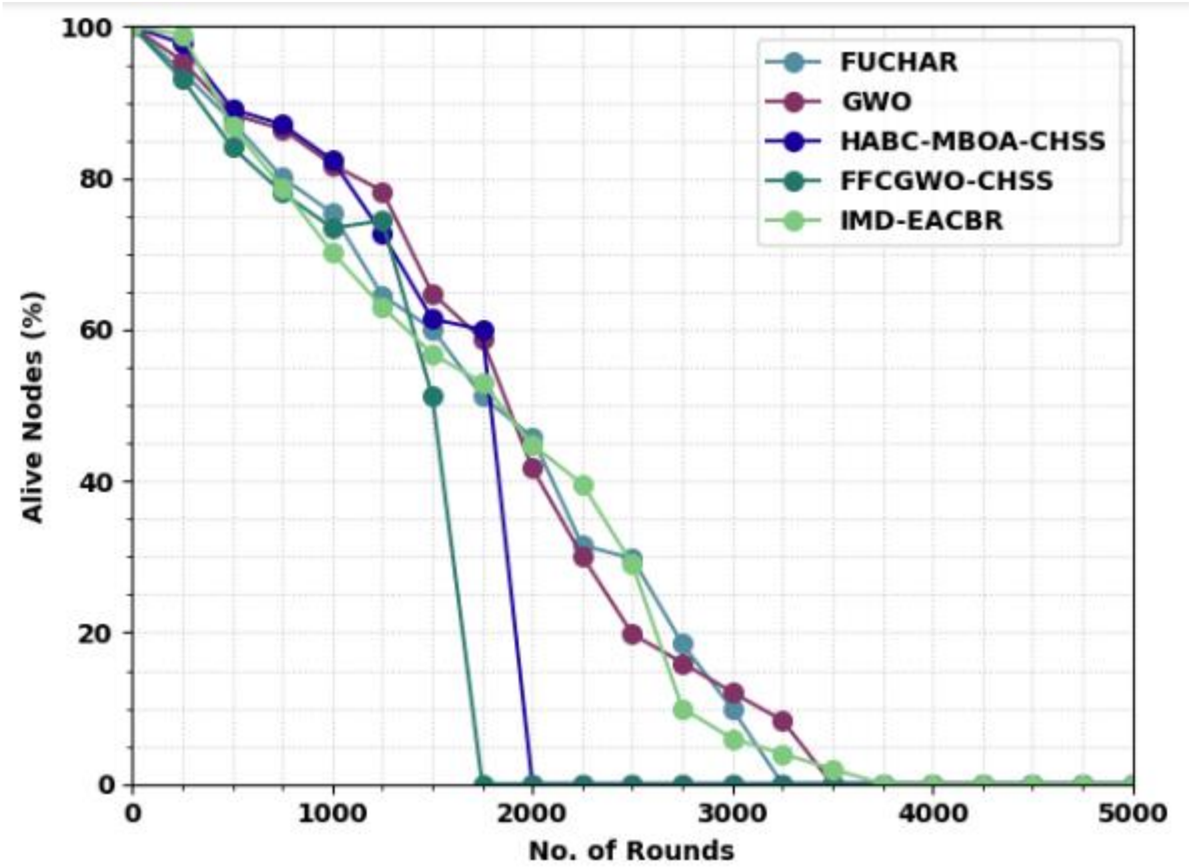

Fig. 2. ALN analysis of several cluster based routing techniques

Both Table 2 and Figure 3 present the results of an examination into the average residual energy (ARE) of many different cluster-based routing strategies. As a result of these findings, it was discovered that the existing methods have demonstrated higher ARE values in comparison to alternative methodology. As an illustration, the ARE values that the FUCHAR, GWO, HABC-MBOA-CHSS, FFCGWO-CHSS, and IMD-EACBR models have attained on 250 rounds are 0.9805, 0.9831, 0.9660, 0.9095, and 0.9470, respectively. Additionally, the ARE of the FUCHAR, GWO, HABC-MBOA-CHSS, FFCGWOCHSS, and IMD-EACBR methods has increased to 0.9705, 0.9781, 0.8180, 0.8895, and 0.9410, respectively, on a total of 500 rounds. In addition, the ARE values that were achieved by the FUCHAR, GWO, HABC-MBOA-CHSS, FFCGWO-CHSS, and IMD-EACBR procedures on 750 rounds were 0.9655, 0.9681, 0.7430, 0.8655, and 0.8550, respectively. In addition, the ARE values of 0.9605, 0.8981, 0.6015, 0.8625, and 0.8500 have been achieved by the FUCHAR, GWO, HABC-MBOA-CHSS, and FFCGWO-CHSS models on a total of 1000 rounds, respectively. In the end, the ARE values that were reached by the FUCHAR, GWO, HABC-MBOA-CHSS, FFCGWO-CHSS, and IMD-EACBR approaches were 0.9555, 0.8981, 0.6015, 0.8625, and 0.8500, respectively, on a total of 1250 cycles.

Table 2 Evaluation of a number of different cluster-based routing strategies under a variety of different counts of rounds

Average Residual Energy

No. of Rounds	FUCHAR	GWO	HABC-MBOA-CHSS	FFCGWO-CHSS	IMD-EACBR
0	1.0000	1.0000	1.0000	1.0000	1.0000
250	0.9805	0.9831	0.9660	0.9095	0.9470
500	0.9705	0.9781	0.8180	0.8895	0.9410
750	0.9655	0.9681	0.7430	0.8655	0.8550
1000	0.9605	0.8981	0.6015	0.8625	0.8500
1250	0.9555	0.7831	0.5840	0.8055	0.5550
1500	0.9505	0.6481	0.5650	0.7615	0.5280
1750	0.8305	0.5481	0.3940	0.7275	0.3440
2000	0.6805	0.4181	0.3820	0.6615	0.3230
2250	0.6605	0.3481	0.3670	0.6095	0.2840
2500	0.4305	0.1981	0.0200	0.5475	0.2440
2750	0.3605	0.1631	0.0130	0.2445	0.1190
3000	0.3005	0.1281	0.0000	0.2265	0.0230
3250	0.0000	0.0981	0.0000	0.1465	0.0000
3500	0.0000	0.0000	0.0000	0.0275	0.0000
3750	0.0000	0.0000	0.0000	0.0265	0.0000
4000	0.0000	0.0000	0.0000	0.0205	0.0000
4250	0.0000	0.0000	0.0000	0.0045	0.0000
4500	0.0000	0.0000	0.0000	0.0000	0.0000
4750	0.0000	0.0000	0.0000	0.0000	0.0000
5000	0.0000	0.0000	0.0000	0.0000	0.0000

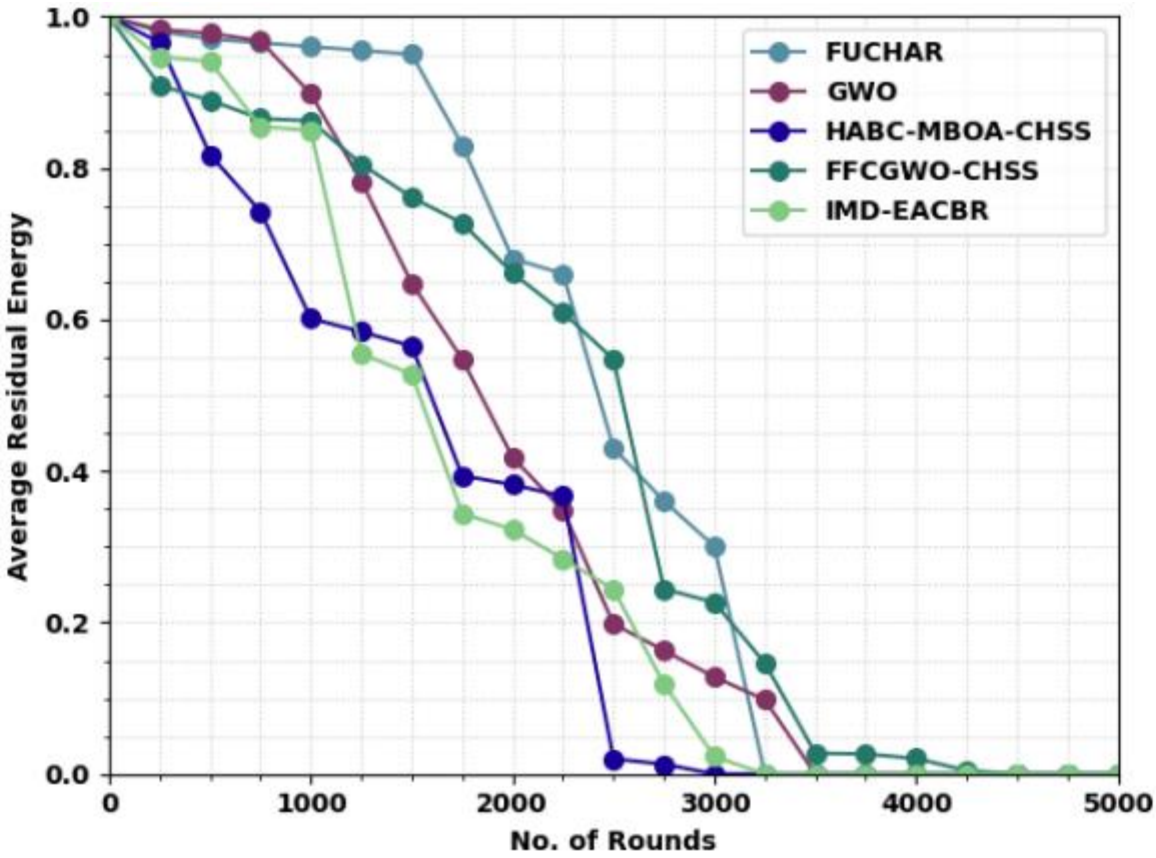

Fig. 3. are an examination of a number of different cluster-based routing strategies

The investigation of the packet delivery ratio (PDR) for a number of different cluster-based routing techniques is performed and presented in Table 3 and Figure 4. Based on these findings, it was discovered that the existing procedures have performed better than the improved PDR values when compared to other methods. By way of illustration, the FUCHAR, GWO, HABC-MBOA-CHSS, FFCGWO-CHSS, and IMD-EACBR models have each obtained a PDR of 98.77%, 98.39%, 96.53%, 95.59%, and 94.39% respectively on 10% of the nodes. Furthermore, the FUCHAR, GWO, HABC-MBOA-CHSS, FFCGWO-CHSS, and IMD-EACBR systems have achieved a PDR of 98.51%, 97.91%, 96.41%, 95.48%, and 94.01% respectively on twenty percent of the nodes.

Table 3 Under different counts of nodes, a PDR study was performed on a number of different cluster-based routing algorithms.

Packet Delivery Ratio(%)					
Nodes (%)	FUCHAR	GWO	HABC-MBOA-CHSS	FFCGWO-CHSS	IMD-EACBR
10	98.77	98.39	96.53	95.59	94.39
20	98.51	97.91	96.41	95.48	94.01
30	98.52	97.59	96.42	95.34	93.72

40	98.20	97.65	96.29	95.13	93.53
50	97.99	97.37	96.04	94.87	93.27
60	97.57	96.55	95.88	94.47	92.85
70	97.14	96.66	95.38	94.31	92.65
80	97.00	96.11	95.02	94.00	92.56
90	96.50	95.15	94.60	93.50	92.27
100	96.63	95.18	94.72	93.50	92.37

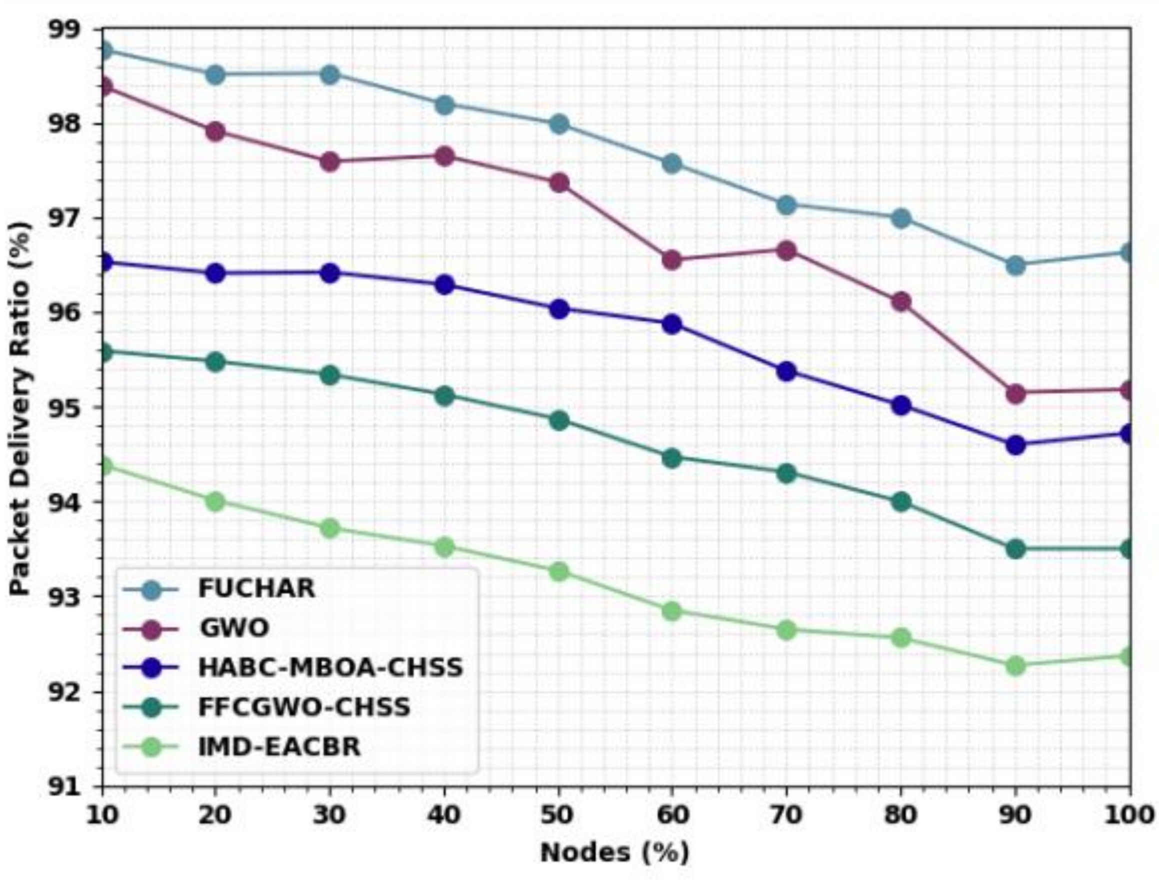

Fig. 4. PDR analysis of several cluster based routing techniques

Conclusion

Routing in wireless sensor networks (WSNs) remains a difficult and critical subject due to the inherent limitations and dynamic nature of these networks. Efficient routing protocols are essential for WSNs to maximize their working lifetime, reliability, and performance, which is becoming increasingly important as their applications become more demanding and diverse. This study tested the efficacy of metaheuristic algorithms in WSN routing with the goals of improving its energy efficiency, scalability, reliability, and adaptability. While Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization

(ACO), and Simulated Annealing (SA) are all well-known metaheuristic methods, applying any one of them without the others might lead to undesirable results. Traditional metaheuristics provide a good foundation, but they can't keep up with the evolving demands of WSNs without significant improvement. An improved metaheuristic approach including hybrid techniques was proposed to solve the drawbacks of each individual metaheuristic strategy. Because it makes use of hybridization and dynamic adaptation techniques, the routing protocol can adjust to new network circumstances while maintaining peak performance. Energy efficiency, data transmission speeds, and node load distribution are just a few of the aspects that can be evaluated in real time thanks to multi-objective optimization. Network performance and routing efficiency are both substantially improved by the improved metaheuristic approach, according to the study's experimental results. Specifically, the proposed method outperforms traditional metaheuristic algorithms in terms of dynamic situation adaptability, data delivery reliability, and network longevity. In conclusion, the challenges of WSN routing may be effectively and dependably addressed by using advanced metaheuristic approaches. By combining several optimization methods, we may create routing protocols that are both efficient and able to withstand the complexities of modern WSN systems. Our study lays the groundwork for future research and development in the field, which will allow for the possibility of more advanced and successful WSN routing solutions in the future.

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