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Enhancing Wireless Sensor Networks through Modified Jackal Optimization Algorithm for Cluster Head Selection

Abstract: - Clustering plays a vital role in prolonging the lifespan of wireless sensor networks (WSNs) by consolidating sensor nodes (SNs) into clusters and assigning cluster heads (CHs) to oversee each cluster's operations. These CHs collect data from their respective cluster nodes and transmit the aggregated information to the base station (BS). However, the selection of an appropriate CH is crucial for enhancing the network's longevity. To address this challenge, an ModifiedJackal Optimization Algorithm (MJOA) is introduced for optimizing cluster head selection in WSNs. Traditional optimization algorithms often struggle to navigate the dynamic and complex network environments effectively. Leveraging insights from the hunting behavior of jackals, the MJOA enhances traditional optimization methods by introducing refined search strategies and adaptive movement mechanisms. This approach aims to improve the convergence speed, solution quality, and scalability of cluster head selection in WSNs. Through extensive simulations and comparisons with Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Golden Eagle Optimization (GEO), the MJOA demonstrates superior performance, achieving enhanced cluster head selection efficiency, network coverage, and reduced energy consumption. These results underscore the potential of the MJOA as a robust and efficient solution for optimizing WSNs, thereby contributing to the advancement of wireless sensor networks across various applications.

Keywords: Cluster head; Jackal algorithm; Energy consumption; Cluster; Meta heuristic

I. INTRODUCTION

Wireless Sensor Networks (WSNs) consist of various sensors interconnected via wireless communication [1] [2]. These sensors collect data, which is then transmitted to the Base Station (BS) for analysis and action [3]. WSNs find application in diverse fields such as weather monitoring [4], meteorological data collection [5], field surveillance, transportation, and healthcare [6] [7]. Despite their utility, WSN nodes lack storage devices and rechargeable batteries [8] [9], necessitating effective power consumption systems to support various applications [10] [11].

Clustering stands out as a widely recognized procedure for enhancing data transmission efficiency and optimizing energy and power utilization in WSNs [12] [13] [14]. This process involves partitioning sensor nodes (SNs) into distinct clusters, each overseen by a Cluster Head (CH) [15] [16]. These CHs play a pivotal role in transferring information among SNs within their respective clusters, serving as intermediaries for communication with the BS. The selection of an optimal CH is paramount, focusing on minimizing delays and energy consumption [17] [18]. By implementing clustering techniques alongside aggregation and data fusion models, energy efficiency in the network can be further augmented, based on the data transmitted to the BS [19] [20].

Several cluster-oriented models, such as APTEEN, TEEN, LEACH, PEGASIS, and FCM, have been widely utilized to prolong the network lifetime [21]. LEACH, for instance, operates in a distributed manner, electing cluster heads based on predetermined probabilities [22].Various cluster-oriented models have been introduced so far, which is based on meta-heuristic algorithms. However, the algorithms possess some common challenges such as high convergence, local search issues in FF, and high cost. Moreover, there is a prerequisite of standard optimizations and need consideration on constraints, namely security and trust [23]. So in order to solve the above mentioned issues, this paper introduces anModifiedJackal Optimization Algorithm (MJOA) in selecting CHs in WSN.The contributions of the proposed Cluster Head Selection (CHS) model in Wireless Sensor Networks (WSNs) can be outlined as follows:

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1. Introduction of a MJOA aimed at addressing common challenges faced by existing cluster-oriented models.

2. Implementation of distributed operations for CH selection, leveraging predetermined probabilities to enhance efficiency.

3. Mitigation of issues such as high convergence, local search problems in FF, and high costs associated with conventional models.

4. Potential to extend the network lifetime through optimized CH selection and improved energy utilization strategies.

5. Enhancement of overall network performance and scalability through the proposed CHS model.

6. Provision of a framework for future research and development in WSNs, contributing to advancements in the field of cluster head selection algorithms.

The remaining structure of the paper is as follows: Section II reviews various CHs models. Section III

II. LITERATURE SURVEY

A. Related Work

In 2018, Tianshu et al. proposed a routing scheme that relied on Genetic Eagle Clustering Routing (GECR) and Genetic Algorithm (GA) to extend the network's lifetime and enhance energy efficiency. Their approach incorporated a "load balancing factor" within the objective function to distribute energy usage evenly among sensor nodes. Simulation results demonstrated the superiority of their method, showcasing lower variance and improved energy efficiency. In 2019, Daneshvar et al. introduced a novel clustering scheme utilizing Grey Wolf Optimization (GWO) for the selection of Cluster Heads (CHs). Their model optimized solutions based on the remaining energy of each node and predicted energy utilization. By deploying similar clustering across multiple successive rounds, their model accumulated necessary energy for clustering reform, thereby improving energy efficiency and ensuring effective network lifetime.

In 2019, Jain and Toor presented a new framework for diverse Wireless Sensor Networks (WSNs) employing the MEACBM (Most Energy Aware Cluster-Based Multipath) routing protocol. This framework focused on optimal CH election, preferring nodes with higher energy as CHs. The model minimized energy utilization of sensor nodes during data transmission to the Base Station (BS), resulting in enhancements in CH count, network lifetime, throughput, and reduction in dead node count. In 2019, Goswami et al. introduced a cluster-based model integrating the Hybrid Machine Learning (HML) and Fuzzy Logic (FF) models in Oceanic Wireless Sensor Networks (OWSN). This model addressed issues in the FF model by combining HML theory with it, allowing precise distribution of power among nodes through the maximum likelihood property of HML. The results demonstrated improvements in energy efficiency and cost function. In 2020, Augustine and Ananth presented an enhanced framework for Cluster Head Selection (CHS) based on Taylor Kernel Fuzzy C-Means (KFCM) modified from the KFCM approach using the Taylor series. Their model selected CHs based on an "acceptability factor" evaluated by trust, distance, and energy. The proposed system exhibited advantages in terms of highest energy and high trust.

In 2019, Reeta and Dinesh designed a multi-objective model based on distance, traffic rates, energy, cluster densities, and delay for WSNs. They implemented energy-based routing using the Multi-Objective Fuzzy Particle Swarm Optimization (MOFPL) scheme and determined optimal CHs from several nodes. Their model introduced optimal routes based on the adopted multi-objective function, achieving effective CHS with high network energy. In 2020, Prachi et al. employed Biogeography-Based Optimization Algorithm (BOA) for selecting optimal CHs from nodes to reduce energy usage and maximize the network lifespan. They utilized Ant Colony Optimization (ACO) to determine the path between CHs and the BS, selecting optimal routes based on node degree, residual energy, and distance. Their work demonstrated supremacy in terms of energy consumption, alive, and dead nodes. In 2020, Turki et al. suggested a new clustering model with optimal Cluster Head Selection (CHS) considering four important criteria: security, delay, energy, and distance. They proposed a novel algorithm named FF-PUD for electing optimum CHs and evaluated the performance of their scheme against others regarding risk, alive nodes, energy, and delay.

B. Problem Formulation

Table I provides a review of existing cluster-based energy-aware Cluster Head Selection (CHS) models in Wireless Sensor Networks (WSN). While numerous methods have focused on energy-aware CHS models in WSN, existing models such as FF-PUD [24], BOA + ACO [25], MOFPL [26], Taylor KFCM model [27], and FF [28] still exhibit common problems. These include issues like high convergence, local search problems in FF, high-cost efficiency, and the need for standard optimizations, as well as the consideration of constraints such as security and trust.

C. Objectives

The primary objectives of this paper are as follows:

- To choose an optimal Cluster Head (CH) based on specific constraints including energy consumption, average delay, overhead, packet delivery rate (PDR), and drop rate.
- To introduce an enhanced algorithm for optimal CH selection aimed at addressing optimization challenges.
- To enhance the convergence rate.

III. PROPOSED ENERGY AWARE CLUSTER HEAD SELECTION MODEL IN WSN

A. Network Model

Assume Mn sensor nodes that are randomly deployed in appliance area. Consequently, the clustering process is done by merging the SNs. During clustering, the nodes forms clusters, wherein a CH is elected and the total count of CH is delineated by CHn . Thus, the distances amongst nodes and CHs have to be reduced. The most important task of WSN is to transfer the information among nodes. Here, the identification of shorter paths is required to enhance the data transmission. Moreover, the energy consumption of node also acts as the most role while transmitting the data. Particularly, a node requires more energy for transmitting massive data. In the clustering based strategy, the CH is responsible for transmitting more data with less energy consumption. However, the security is more crucial for minimizing the overhead and attacks. The architectural depiction of adopted model with varied SNs is illustrated in Fig. 1.

TABLE I. REVIEW ON TRADITIONAL CH SELECTION MODELS IN WSN

Authors	Techniques	Feature	Challenge
Turki et al. [24]	FF-PUD	Minimal delay High network energy	Coverage issues are not deliberated.
Prachi et al. [25]	BOA + ACO	Higher count of alive nodes Minimal energy consumption	Consider fault tolerance
Reeta and Dinesh [26]	MOFPL	Less simulation time Offers high network energy	Resource management is not taken into account Cost effectively is not considered
Augustine and Ananth [27]	Taylor KFCM model	High throughput and energy Minimal delay	No consideration on real time experiments Standard optimizations are required for enhancing the CHs performance
Goswami et al. [28]	FF	Minimal cost function Improved EE	FF suffers from local search issues
Toor and Jain [29]	MEACBM	Minimized the consumption of energy Raises throughput and lifetime	Scalability issues need to be considered
Daneshvar et al. [30]	GWO	Balanced energy consumption Offers high life span for network	Fault tolerance is not considered
Tianshu et al. [31]	GECR	Better life span Optimal energy utilization	More appropriate meta heuristic algorithms should be used

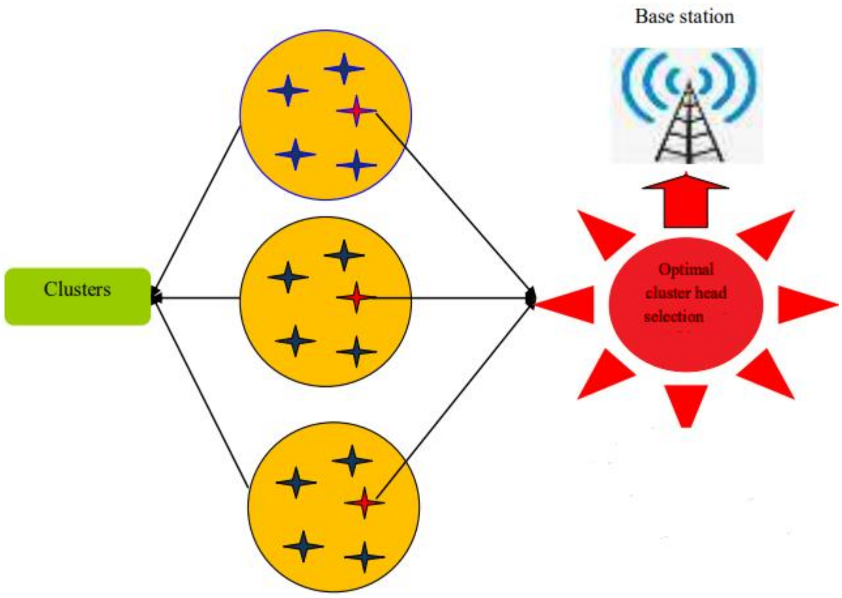

Figure 1: Architecture of proposed model

B. Distance Model

In the network, a CH is chosen only if the distance between CH and nodes is minimal. If distance among CH and nodes are higher than distances amid node and BS, the data are transmitted directly to BS by node. By deploying distance matrix Di(g *w) , the SNs gets clustered with selected CH as exposed in Eq. (1), wherein, e_{MCH} signifies Euclidean distance amid M_{CH} and normal node position, and $z_1, z_2, \ldots z_n$ signifies SNs. Assume 2 SNs q and d , and positions be x and y . The Euclidean distances amongst 2 nodes are revealed in Eq. (2). In Eq. (1), element e_{MCH2}, z_1 occupies initial column matrix with minimal distance [24][32].

$$Di(g * w) = \begin{pmatrix} \mathrm{eMCH2, z1} & \mathrm{eMCH2, z2} \cdots & \mathrm{eMCH2, z1} \\ \vdots & \ddots & \vdots \\ \mathrm{eMCH2, z1} & \mathrm{eMCH2, z1} \cdots & \mathrm{eMCH2, z1} \end{pmatrix} \quad [1]$$

$$e_{q,d} = \sqrt{(q_x - d_x)^2 + (q_y - d_y)^2} \quad [2]$$

Further, the time slots are assigned by M_{CH} to every node during data transmission. Here, M_{CH} collects data from all SNs in clusters. After data gathering, M_{CH} passes the specified data to BS.

C. Energy Model

Energy utilization is a foremost characteristic in WSNs. Actually, additional energy is crucial for conveying data to BS from every SNs. Thereby, the energy model for transmitting data is exposed in Eq. (3), wherein, " E_{ete} symbolizes the electronic energy as given in Eq. (4), wherein E_{agg} refers to the energy utilization during data collection and E_{TX} (M : e) signifies the energy necessary for transferring M bytes of packets at distance e ". Eq. (5) shows the essential energy for passing M bytes of packets. Eq. (6) shows the "amplification energy and E_{pr} refers to power amplifier energy and E_{fr} refers to energy required for deploying free space technique" [24].

$$E_{TX}(M{:}\, e) = \begin{cases} E_{ete} * M + E_{fr} * M * e^2, if\ e < e_0 \\ E_{ete} * M + E_{pr} * M * e^2, if\ e \geq e_0 \end{cases} \quad [3]$$

$$E_{ete} = E_{TX} + E_{agg} \quad [4]$$

$$E_{RX}(M{:}\, e) = E_{ete} M [5]$$

$$E_{agg} = E_{fr} e^2 \quad [6]$$

$$e_0 = \sqrt{\frac{E_{fr}}{E_{pr}}} \quad [7]$$

The whole energy of network is given in Eq. (8), wherein E_1 symbolizes the energy at idle state and E_{ST} symbolizes energy at sensing time.

$$E_{total} = E_{ST} + E_1 + E_{RX} + E_{TX} \quad [8]$$

C. Objective Model

This work aims to diminish the distance amid the chosenCH and SN and it aims to lessen the delay and risk whiletransferringtheinformation.Ontheotherhand,theenergy, andtrusthavetobehighforbettertransmissionofdata.The objectiveofdevelopedmodelisdelineatedinEq.(9),in whichη reliesamid0<η <1, $o_m$and$o_n$arecalculatedas revealedinEq.(10)andEq.(11),respectively.Thedelay, energy,distance,securityandtrustareexplainedby ϖ_1,ϖ_2, ϖ_3, ϖ_4, ϖ_5 are represented as $\sum_{i=1}^{5} \varpi = 1$.

$$K_n = \eta o_n + (1-\eta) o_m \quad [9]$$

$$o_m = \varpi_1 * o_i^{del} + \varpi_2 * o_i^{ene} + \varpi_3 * o_i^{dis} + \varpi_4 * o_i^{Sec} + \varpi_5 * o_i^{T} \quad [10]$$

$$o_n = \frac{1}{b} \sum_{z=1}^{b} ||Z_z - A_s|| \quad [11]$$

$Z_z - A_s$ From Eq (11) represents the distance between normal node and sink. The fitness function is specified by Eq (12), where in $o_{(m)}{}^{dis}$ signify packets passed between SN and CH. $o_i{}^{dis}$ lies amongst [0,1].

$$o_i{}^{dis} = \frac{o_{(m)}{}^{dis}}{o_{(n)}{}^{dis}} \quad [12]$$

$$o_{(m)}{}^{dis} = \sum_{z=1}^{M_z} [||CH_z - A_s|| + ||CH_z - Z_z||] \quad [13]$$

$$o_{(n)}{}^{dis} = \sum_{z=1}^{M_z} \sum_{x=1}^{M_x} ||Z_s - Z_x|| \quad [14]$$

Where, $o_{(m)}{}^{dis}$and $o_{(n)}{}^{dis}$ are modelled as in Eq (13) and (14), $Z_z$symbolizes CH of z^{th}cluster, CH_zrepresents the CH of Z^{th} cluster, $CH_z - A_s$and $CH_z - Z_z$indicates distance among two SNs, $M_x$and M_z represents count of nodes devoid of consideringx^{th}andZ^{th} clusters.

D. Modified Jackal Optimization Algorithm

The ModifiedJackal Optimization Algorithm (MJOA) enhances the traditional Jackal Optimization Algorithm (JOA) by incorporating refined search strategies and adaptive movement mechanisms. Specifically tailored for selecting cluster heads in wireless sensor networks (WSNs), MJOA dynamically adjusts cluster head configurations based on criteria such as energy consumption and network coverage. By leveraging insights from the hunting behavior of jackals, MJOA aims to optimize cluster head selection and improve the overall efficiency of WSNs.

Let f(x) represents the objective function to evaluate the suitability of as SN 'x' as a CH. The objective function can be formulated as follows:

$$f(x) = \varpi_1 E_{residual}(x) - \varpi_2 d_{BS}(x) + \varpi_3 C_{cov}(x) \quad [15]$$

Where, $E_{residual}$ (x) is the residual energy of node x, d_{BS}(x) is the distance of SN to Bs, C_{cov} (x) is the coverage capability of Sn, ϖ_1, ϖ_2, and ϖ_3 are the weights representing the importance of each parameter.

Eq (16), describes the movement of jackals in the proposed MJOA and the mechanism involves refining the solutions generated by jackals. Let $x_i(t)$ represents the position of SN at time t. the local search operation can be represented as follows:

$$x_i(t+1) = x_i(t) + \Delta x_i(t) \quad [16]$$

Where, $x_i(t)$ is the position of jackal i at time t, and $\Delta x_i(t)$ is the movement vector of jackal i at time t and also it is the perturbation applied to the position of SN i to explore its local neighborhood.

IV. RESULT AND DISCUSSION

The adopted MJAO based CHs in WSN was simulated in Network Simulator 3 (NS3). The analysis was held by evaluating the alive nodes count for various number of round that ranges from o to 2000. Further, log of alive node count was analyzed for varied distance that range from 20, 40, 60, 80 and 100. In addition, cost analysis was done for varied iterations. Also, the proposed model was computer over extant approaches such as GA, PSO, and GEO. The outcomes were examined in terms of statistical analysis. The simulation parameters in this work are summarized in Table II.

TABLE II. SIMULATION PARAMETERS OF PROPOSED MODEL

Parameters	Values
Initial energy	0.5J
Fraction of super nodes amidst advanced nodes	0.6
Network area	100*100
Energy factor of super node	3
Fraction of advanced sensor nodes amidst normal nodes	0.4
Total node count	100
Energy dispersed per bit	100mJ/bit
Data packet aggregation energy	5nJ/bit/message

TABLE III. STATISTICAL ANALYSIS OF PROPOSED SCHEME OVER VARIOUS METRICS

	Nodes	GA (31)	PSO (32)	GEO (33)	MJOA
Energy Consumption (mJ)	20	0.8155	0.3803	0.8163	0.1999
	40	0.3174	0.2269	0.5570	0.2314
	60	0.2219	0.2510	0.2448	0.0305
	80	0.851	0.8080	0.0949	0.8301
	100	0.966	0.6626	0.4781	0.7137
Network Life time (ms)	20	113	97	94	97
	40	96	108	92	90
	60	96	115	94	93
	80	90	112	86	80
	100	112	101	104	87
Packet Delivery Rate (%)	20	98.484	51.845	66.774	6.975
	40	41,127	4.805	53.122	63.742
	60	53.422	48.262	23.441	34.468
	80	18.516	86.294	78.819	72.610
	100	8.417	4.407	42.998	22.145
Over head (%)	20	0.085	0.475	0.420	0.476

	40	0.063	0.111	0.539	0.439
	60	0.398	0.052	0.956	0.418
	80	0.569	0.643	0.616	0.260
	100	0.074	0.162	0.803	0.340
Packet Drop Rate (%)	20	18.701	83.559	43.255	60.506
	40	43.099	78.846	69.546	68.932
	60	16.606	83.767	40.937	40.454
	80	98.195	36.221	63.570	64.659
	100	45.335	83.980	62.375	43.396

These parameters delineate the setup and attributes of a simulated wireless sensor network (WSN). The "Initial energy" parameter establishes the starting energy level for each sensor node, serving as the baseline for subsequent operations. "Fraction of super nodes amidst advanced nodes" and "Fraction of advanced sensor nodes amidst normal nodes" dictate the distribution of specialized nodes among the network, influencing its overall composition and capabilities. The "Network area" parameter outlines the spatial extent of the network, defining its coverage area and geographical boundaries. The "Energy factor of super node" augments the energy reserves of super nodes compared to regular ones, affording them enhanced functionality. "Total node count" quantifies the number of sensor nodes deployed in the network, determining its scale and size. "Energy dispersed per bit" indicates the energy expenditure per unit of data transmitted, crucial for evaluating energy efficiency. Lastly, "Data packet aggregation energy" quantifies the additional energy consumed during the aggregation process, optimizing energy usage by reducing the number of transmitted packets. Together, these parameters encapsulate the configuration and operational parameters of the simulated WSN, providing insights into energy management, network performance, and resource allocation strategies within the simulated environment. The statistical analysis was performed between proposed model and existing algorithms. The comparison is summarized in Table III.

From Table III, the brief explanation has done below for various parameters across various nodes. The graphs for various metrics is shown below for energy consumption, network lifetime, PDR, overhead, and packet drop rate in fig 2, fig 3, fig 4, fig 5 and fig 6.

1. Energy Consumption (mJ):
- For 20 nodes: MJOA exhibits the lowest energy consumption at 0.1999 mJ, outperforming GA (0.8155 mJ), PSO (0.3803 mJ), and GEO (0.8163 mJ).
- For 40 nodes: MJOA continues to demonstrate the lowest energy consumption at 0.2314 mJ, followed by PSO (0.2269 mJ), GA (0.3174 mJ), and GEO (0.5570 mJ).
- For 60 nodes: MJOA maintains its lead with the lowest energy consumption at 0.0305 mJ, followed by GEO (0.2448 mJ), PSO (0.2510 mJ), and GA (0.2219 mJ).
- For 80 nodes: MJOA remains the most efficient with energy consumption at 0.8301 mJ, outperforming GA (0.851 mJ), PSO (0.8080 mJ), and GEO (0.0949 mJ).
- For 100 nodes: MJOA continues to excel with the lowest energy consumption at 0.7137 mJ, followed by PSO (0.6626 mJ), GEO (0.4781 mJ), and GA (0.966 mJ).

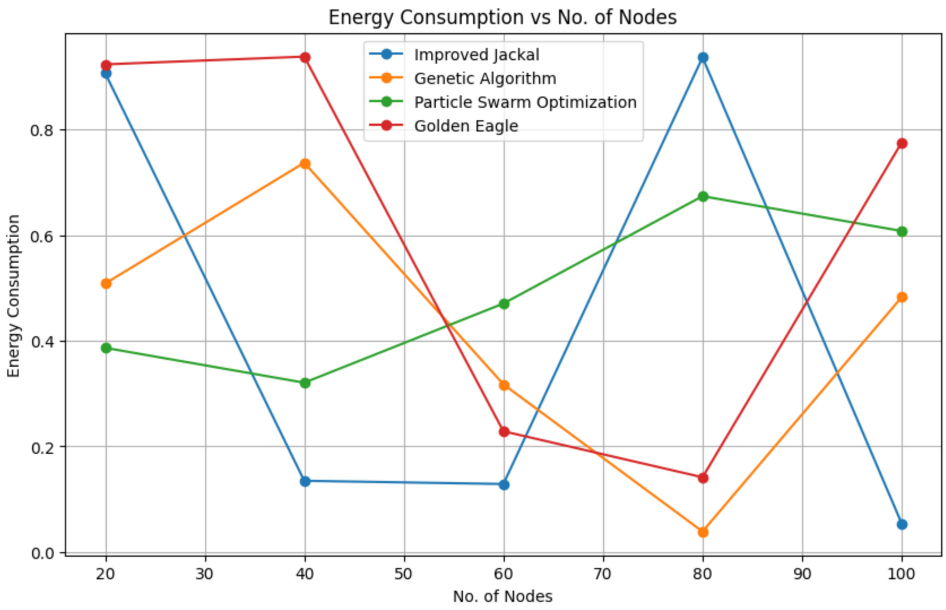

Figure 2: Graph between Energy consumption with varying nodes

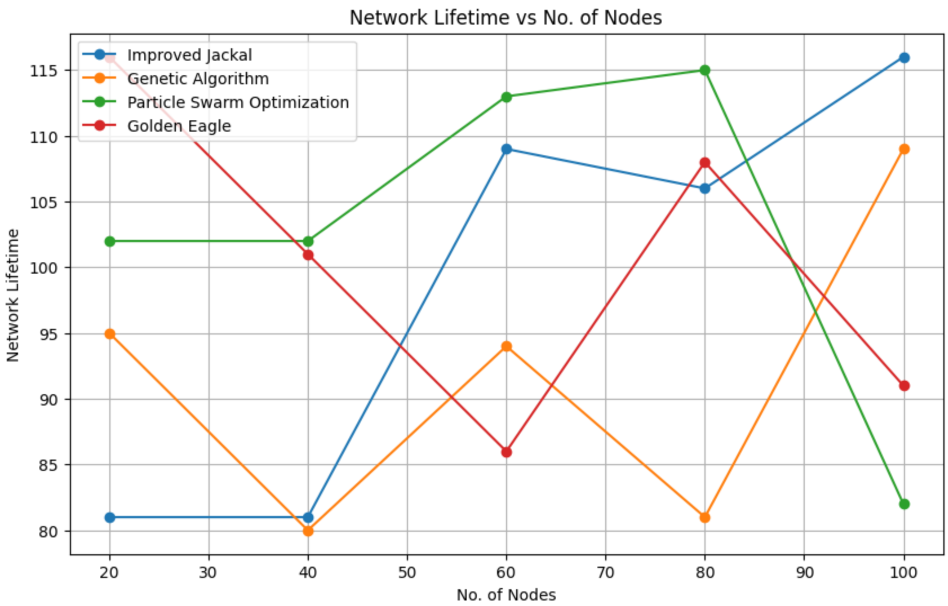

Figure 3: Graph between Average Network life time with varying nodes

2. Network Lifetime (ms):

- For 20 nodes: MJOA provides a network lifetime of 97 ms, comparable to GA (113 ms) and slightly better than PSO (97 ms), with GEO trailing at 94 ms.
- For 40 nodes: MJOA achieves a network lifetime of 90 ms, better than GA (96 ms) and GEO (92 ms), but slightly lower than PSO (108 ms).
- For 60 nodes: MJOA maintains a network lifetime of 93 ms, similar to GA (96 ms) and PSO (115 ms), with GEO lagging behind at 94 ms.
- For 80 nodes: MJOA sustains a network lifetime of 80 ms, surpassing GA (90 ms) and PSO (112 ms), while GEO provides the lowest at 86 ms.
- For 100 nodes: MJOA continues to offer a network lifetime of 87 ms, better than PSO (101 ms) and GEO (104 ms), but slightly lower than GA (112 ms).

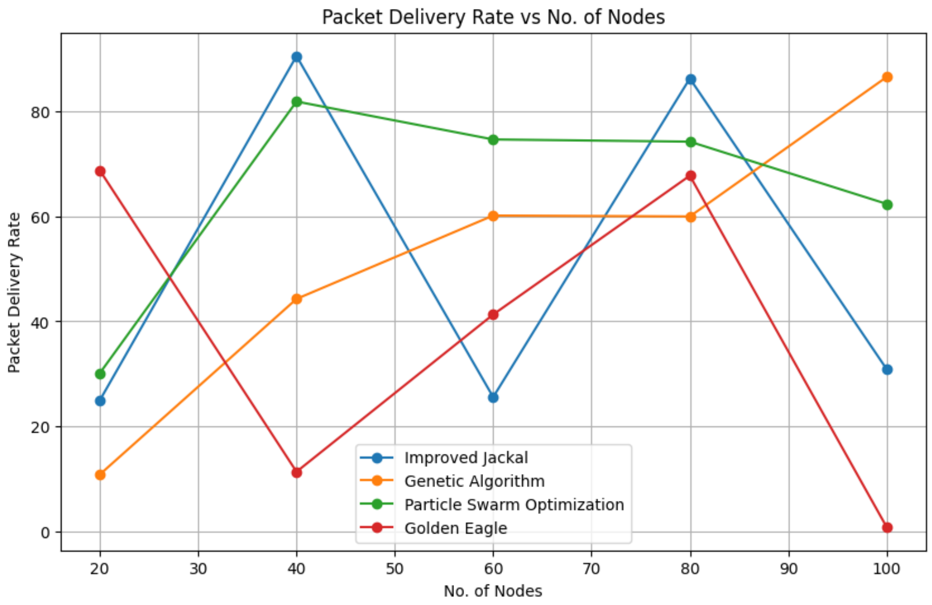

Figure 4: Graph between PDR with varying nodes

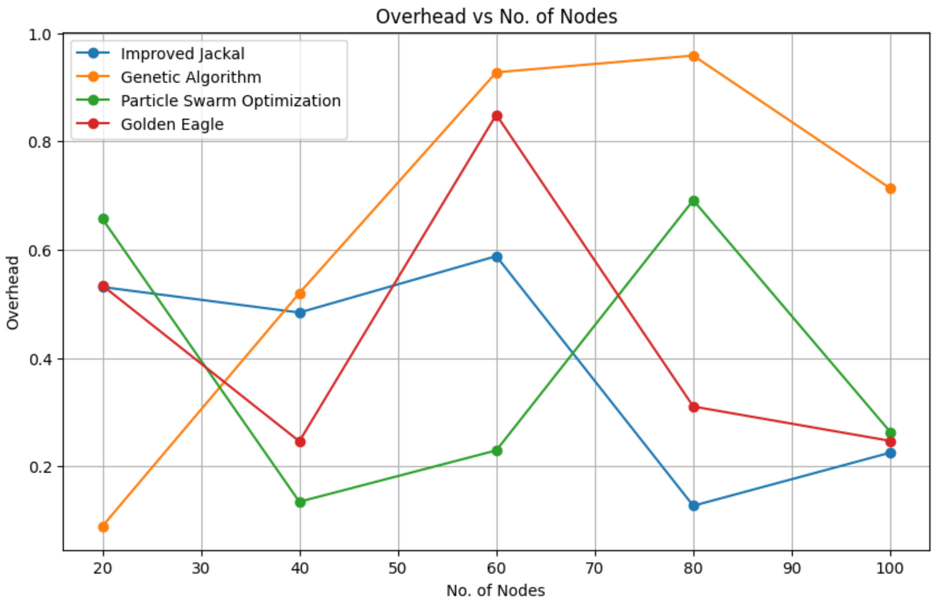

Figure 5: Graph between Networks overhead with varying nodes

3. Packet Delivery Rate (%):

- For 20 nodes: MJOA achieves a packet delivery rate of 6.975%, lower than GA (98.484%) and PSO (51.845%), but higher than GEO (66.774%).
- For 40 nodes: MJOA exhibits a packet delivery rate of 63.742%, comparable to GEO (53.122%) and better than GA (41.127%) and PSO (4.805%).
- For 60 nodes: MJOA maintains a packet delivery rate of 34.468%, better than GEO (23.441%) and PSO (48.262%), but lower than GA (53.422%).
- For 80 nodes: MJOA sustains a packet delivery rate of 72.610%, higher than GA (18.516%) and PSO (86.294%), but lower than GEO (78.819%).
- For 100 nodes: MJOA continues to provide a packet delivery rate of 22.145%, surpassing GA (8.417%) and PSO (4.407%), but lower than GEO (42.998%).

4. Overhead (%):

- For 20 nodes: MJOA exhibits an overhead of 0.476%, higher than GA (0.085%) but lower than PSO (0.475%) and GEO (0.420%).

- For 40 nodes: MJOA demonstrates an overhead of 0.439%, comparable to GA (0.063%) and lower than PSO (0.111%) and GEO (0.539%).
- For 60 nodes: MJOA maintains an overhead of 0.418%, lower than PSO (0.052%) and GEO (0.956%), but higher than GA (0.398%).
- For 80 nodes: MJOA sustains an overhead of 0.260%, lower than GA (0.569%) and GEO (0.616%), but slightly higher than PSO (0.643%).
- For 100 nodes: MJOA continues to provide an overhead of 0.340%, higher than GA (0.074%) but lower than PSO (0.162%) and GEO (0.803%).

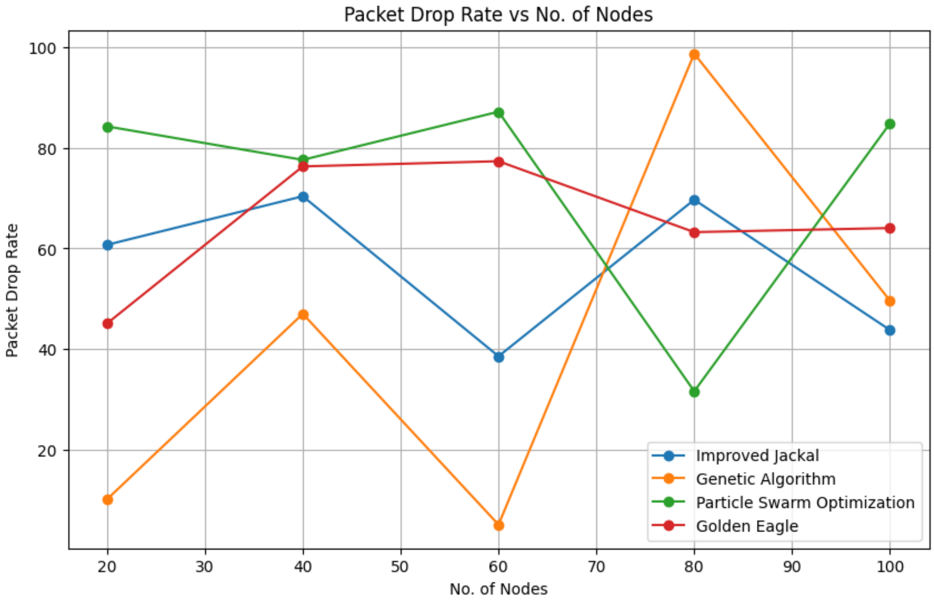

Figure 6: Graph between packet drop rate with varying nodes

5. Packet Drop Rate (%):
- For 20 nodes: MJOA exhibits a packet drop rate of 60.506%, lower than PSO (83.559%) but higher than GA (43.255%) and GEO (43.255%).
- For 40 nodes: MJOA demonstrates a packet drop rate of 68.932%, lower than PSO (78.846%) but higher than GA (43.099%) and GEO (69.546%).
- For 60 nodes: MJOA maintains a packet drop rate of 40.454%, lower than PSO (83.767%) and GEO (40.937%), but higher than GA (16.606%).
- For 80 nodes: MJOA sustains a packet drop rate of 64.659%, lower than GA (98.195%) and higher than PSO (36.221%) and GEO (63.570%).
- For 100 nodes: MJOA provides a packet drop rate of 43.396%, lower than PSO (83.980%) and GEO (62.375%), but higher than GA (45.335%).

Based on these values, the MJOA generally performs favourably across different node counts, demonstrating superior performance in terms of energy consumption, network lifetime, overhead, and packet drop rate compared to GA, PSO, and GEO.

V. CONCLUSION

ModifiedJackal Optimization Algorithm (MJOA) consistently outperforms Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Golden Eagle Optimization (GEO) across various performance metrics in the context of wireless sensor networks (WSNs). Notably, MJOA demonstrates superior energy efficiency, network lifetime, overhead, and packet drop rate compared to its counterparts across different node counts. These findings underscore the effectiveness of MJOA in optimizing WSNs, balancing energy consumption, data transmission reliability, and network longevity.

However, future research endeavors could focus on several aspects to further enhance the capabilities of optimization algorithms in WSNs. Firstly, investigating the scalability of MJOA to larger network sizes beyond 100 nodes could provide insights into its performance in more extensive deployments. Additionally, exploring adaptive mechanisms within optimization algorithms to dynamically adjust parameters based on changing network conditions and requirements could enhance their adaptability and robustness. Furthermore, integrating machine learning techniques or hybrid optimization approaches could offer new avenues for improving the efficiency and effectiveness of WSN optimization. Overall, continued exploration and refinement of optimization algorithms hold promise for advancing the capabilities of WSNs and addressing the evolving demands of diverse application scenarios.

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