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An Advanced Approach of Optimal Routing Protocol for WSN Using Grey Wolf Optimizer

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Abstract

This study investigates the performance of an optimal routing protocol in Wireless Sensor Networks (WSNs) based on the Grey Wolf Optimizer (GWO), which is considered an outstanding Metaheuristic optimization technique. Unlike numerous previous studies, this research develops an advanced approach by optimizing the cluster head nodes and sink node mobility, which are essential elements for achieving an optimal routing protocol in WSNs. Several crucial factors, including the rate of energy consumption, and others are considered to ensure trustworthy routing. To demonstrate the feasibility of the proposed approach, three other methods are utilized in a comparative study. Various evaluation measures are exploited, including the number of alive nodes, mean throughput, probability of avoiding unsuitable cluster heads, energy consumption, and computation cost. The simulation results clearly reveal the superiority of the GWO compared to the aforementioned schemes over 5000 implementation rounds. Throughout the simulations, the total number of nodes (700) in the proposed WSN remained operational up to 4500 rounds, with the attained throughput staying above 1000 (bit/sec). Notably, the number of dead nodes remains at 0 after 1500 rounds. Moreover, the probability of avoiding unsuitable cluster heads is the highest, and the packet delivery ratio consistently remains at or above 68%. Additionally, the energy consumption of nodes achieved by the GWO is the lowest and does not exceed 200 Joules, while the computational cost significantly declines to reach 30.5%.

Keywords- computational cost, cluster heads, sink node mobility, energy consumption, routing protocol.

I. INTRODUCTION

Wireless Sensor Networks (WSNs) have experienced significant advancements and find application in various fields such as environmental monitoring, security, and military operations [1-5]. These networks are composed of sensor nodes with limited energy, reduced processing capabilities, and low-cost components [6-8]. The effectiveness of WSNs in performing specific tasks relies heavily on the energy capacity of the sensor nodes, their data transmission capabilities, and their ability to relay data to the central sink node [9-11]. To evaluate the feasibility of the routing protocol in WSNs, several metrics such as energy consumption of nodes, computational cost, throughput, and packet delivery ratio are considered. In practice, the energy consumption within the network is directly influenced by the distance between nodes. A rise in distance between two nodes results in a higher rate of energy consumption [12-14]. To address this challenge, clustering technique is considered a feasible solution to stabilize the energy consumption in WSN. In this regard, numerous literature have been conducted using different methodologies in order to minimize the energy consumption and hence, the lifespan of WSN is noticeably extended [15-21]. Yuan et al. [22] proposed clustering technique based on genetic-algorithm (GA) to achieve an optimal routing protocol considering the energy consumption stability.

The proposed study focused on the arrangement of nodes in applicable clusters and selection of cluster head node that transmits data to reciever. However, the results revealed that the proposed clustering is a highly time consumption and a less feasible with limited network area a. Sarkar and Senthil Murugan [23] proposed an optimal routing protocol based on the cyclic randomization firefly to accomplish an improved data transmission with less energy consumption. The authors utilized the firefly optimization to maximize the lifespan of network. However, the drawbacks of this approach are high computational cost, augmented time complexity and untimely convergence. Barzin et al. [24] optimized a routing protocol using fire fly and shuffled frog-leaping algorithm. The authors optimized a cluster head at each of implementation considering the criteria of cluster load. The attained results revealed that the proposed algorithm is sufficiently feasible to expand the life expectancy of WSN compared to the other methods. However, the low efficiency of throughput and High computational complexity are the main downsides in this study.

Kumaran and Yaashuwanth [25] investigated the performance of a routing protocol by using a hybrid chemical reaction optimization algorithm considering the energy consumption. The attained results showed a noticeable improvement in terms of lifespan, however the drawbacks of this approach are augmented computation cost and reduced packet delivery ratio efficiency. In the same context, a hierarchical layer balanced clustering pattern to optimize the routing protocol in WSN was introduced by Prasad et al. [26]. The authors separated WSNs into diverse size hierarchical layers and maintained the computational complexity. The average packet transmission rate and network lifetime were not harmfully influenced. However, the low packet delivery ratio efficiency is the main shortcoming of this algorithm. Sengathir et al. [27] investigated the performance of a routing protocol using firefly considering cluster head selection to maximize the energy stabiltiy that results in prolonging the lifespan of network. The optimal cluster head is determined by firefly optimization then artificial bee colony optimization is utilized to optimize the data route . The attained results revealed that the lifespan and the energy consumption were remarkably improved. However, the internal nodes distancing, reduced throughput gain and high computational cost are the downsides of this approach.

Khot and Naik et al. [28] proposed an optimal a routing protocol by using hybrid optimization algorithm in order to guarantee a secure routing of data-packet. The authors utilized particle swarm optimization to optimize cluster head, the evaluation of the used fitness function was based on diverse metrics such as maintainability factor, steadiness factor, and trust. Then water wave optimization algorithm was utilized to optimize the route between the cluster head and sink nodes, the attained results proved the feasibility of the proposed approach in terms of energy consumption and number of alive nodes. However, the High computational complexity and the poor performance in the large networks are the main weaknesses. Ajmi et al. [29] proposed an optimal a routing protocol by using a multi-weight chicken-swarm-based genetic algorithm (MWCSGA) considering the energy consumption. The proposed algorithm optimized the cluster heads then the optimal route was determined, the attained results proved the viability of the proposed approach in terms of network throughput, and packet drop. However, a remarkable delay in large network and increased population count are the main weaknesses in this study.

Daniel et al. [30] proposed an optimal routing using the tunicate swarm butterfly optimization algorithm (TSBOA) to prolong the lifespan of WSN. The butterfly optimization algorithm (BOA) and tunicate swarm algorithm (TSA) were integrated to optimize the cluster heads to avoid redundant energy consumption. The evaluation of the used fitness function was based on various factors including delay, link lifespan, expected energy and sensor node energy consumption. The simulation results showed the feasibility of the proposed approach in term of mean throughput and residual energy, however the High computational cost is the main shortcoming in this study. Balamurugan et al. [31] optimized a routing protocol using hybrid group teaching optimization and modified African Buffalo algorithm (HGTO-MABA) to enhance the lifespan of network. The attained results showed a remarkable advancement in throughput, and network lifetime. However, the main drawback was the complexity of the proposed approach to accomplish the balance between energy consumption and data collision prevention. Based on the abovementioned literature, it can be evidently concluded that different aspects including computational cost, energy consumption, and throughput need further improvement to optimize the performance of the routing protocol. Hence, the contributions that characterize this study are as follows:

1. To develop a novel approach using GWO to determine the optimal routing protocol considering lifespan of network and energy consumption.
2. To achieve an optimal routing protocol, the study focuses on determining the optimal cluster head nodes and sink node mobility. This is achieved by developing a fitness function that considers multiple factors, including the rate of energy consumption, and others.
3. To conduct the comparative study between the proposed approach and a number of previous literature by using different evaluation measures including computational cost, energy consumption, and throughput.

II. THE PROPOSED METHODOLOGY

The proposed approach in this study employs GWO to determine the optimal cluster head that significantly enhances optimizing the routing protocol which minimizes the influences of packet loss and energy consumption to ensure trustworthy routing. The entire methodology in this study can be summarized in five stages:

1. The energy consumption of nodes including transmission and reception is modelled.
2. Various nodes are arbitrarily organized in the network while the preliminary location of sink is at a middle of the network. The energy consumption of these nodes are evaluated by the proposed energy model in the first stage.
3. The optimal cluster head is determined by utilizing GWO, it is worth to mention that in this stage the cluster affiliates convey the certain data to the cluster head .
4. The routing protocol is optimized based on the selected cluster head in the previous stage.

A comparative study between the proposed approach and a number of previous literature is conducted based on different measures to demonstrate the viability of the proposed approach.

1. Modelling of energy consumption

The proposed approach utilizes a prevalent model used by numerous studies to express the energy consumption [18–20]. To transmit an amount of 'b' data bits to a particular destination point over the distance (d), the required energy can be evaluated by:

$$E_T(\, b\,.d) = \begin{cases} b\ \times E_{ecn} \ \ + b \times E_f\ \times\ d^2 & .d \le\ d_T \\ b\ \times E_{ecn} \ \ + b \times E_m\ \times\ d^4 & .d >\ d_T \end{cases} \qquad (1)$$

Where E_{ecn} refers to the energy consumed by every node throughout the data communication process. Additionally, E_f and E_m refer to the energy consumed by the nodes in the free space and muti-path propagation respectively.
The threshold value of the distance which is used to select the type of propagation model is evaluate by:

$$d_T = \sqrt{\frac{E_f}{E_m}} \qquad (2)$$

At the destination, the energy consumed to receive 'b' data bits can be expressed by:

$$E_R(\, b) = b\ \times\ E_{ecn} \qquad (3)$$

As explained earlier, the main task of cluster heads is to eliminate a redundant energy consumption throughout data reception from the cluster affiliates (ca). The total energy consumption during data reception can be evaluated by:

$$E_{ch} = \begin{cases} b_{Q_{ca}} \times (E_{ecn} \ \ + E_{agg}\,) + b \times E_f\ \times\ {d_{ch}}^2 & .\ d_{ch} \le\ d_T \\ b_{Q_{ca}} \times (E_{ecn} \ \ + E_{agg}\,) \ \ + b \times E_f\ \times\ {d_{ch}}^4 & .d >\ d_T \end{cases} \qquad (4)$$

Where Q_{ca} refers to the total number of the cluster affiliates (ca) related to a certain cluster head, E_{agg} represents the total energy consumption throughout data aggregation course and d_{ch} is the Euclidean distance between the destination and cluster head .

2. Fitness function

In this study, different factors including rate of energy consumption, and mean node energy are considered to evaluate the fitness of every search agent which is represented by a wolf in the optimization algorithm.

2.1 Rate of Energy Consumption (R_{EC})

In practise, the sensors nodes individually use a certain amount of energy throughout consecutive rounds of execution. It can be represented by the rate of energy consumption (R_{EC}) and evaluated by:

$$R_{EC}\ =\ \sum_{i=1}^{SN_{count}}(\ \ EN_{C(PR)}\ \ -\ \ EN_{C(CR)}\ \ ) \qquad (5)$$

Where $EN_{C(PR)}$ refers to the amount of energy that is available in the sensor node after data transmission in the previous round, $EN_{C(CR)}$ the amount of energy retained by a sensor node in the current round. It is worth to mention that the R_{EC} of every node is computed considering the mean threshold of R_{EC} since the node which has R_{EC} higher than the threshold value maximizes it`s opportunity to be optimized as cluster head.

2.2 Mean Node Energy (SN_{ME})

To eliminate a recurrent selection of the cluster head, the mean node energy should be evaluated throughout optimizing the cluster heads. The nodes can be categorised into excellent, progressive, or ordinary nodes relying on their mean energy. The excellent nodes possess the greatest energy in the network and they are survived in the network for an extensive period, along with the progressive nodes which nodes locate between the ordinary and excellent nodes, since they retain an adequate amount of energy, which ensure their existence in the network. Based on the above, the opportunities of excellent and progressive nodes are higher than those of the ordinary nodes to be optimized as cluster heads in the network. To categorize the nodes in the abovementioned types, their energies are normalized between 0 and 1 by:

$$SN_{ME} = \frac{1}{CL_N}\sum_{i=1}^{CL_N}\ SN_{E(i)} \qquad (6)$$

Where SN_{ME} refers to the mean energy retained by each node, and CL_N and $SN_{E(i)}$ refer to the total number of nodes and energy used by every sensor node, respectively. The node with normalized energy between 0.8 and 1 is categorized as excellent node, while the normalized energy of the progressive node is constrained by 0.6 and 0.8. Lastly, the ordinary node has a normalized energy between 0.5 and 0.6.

2.3 Distance between Sink and Sensor Nodes (D_{SN-BS})

One of the effective parameters in the evaluation of the energy consumption in WSN is the detachment between the sensor nodes and sink. Hence, the median distance between the sensor nodes surviving in the route between them and the sink node should be optimized to accomplish an efficient cluster head selection. The abovementioned median distance can be evaluated by:

$$D_{SN-BS} = \sum_{i=1}^{CL_N} \frac{Dist_{N(i)-S_{NK}}}{Dist_{Mean\ (N(i)-S_{NK})}} \qquad (7)$$

Where $Dist_{N(i)-S_{NK}}$ and $Dist_{Mean\ (N(i)-S_{NK})}$ are the actual Euclidean distance between the i^{th} sensor node and sink and the mean Euclidean distance between the i^{th} sensor node and sink, respectively.

3. Fitness Function for Optimizing Cluster Head Nodes

This approach develops a fitness function covers all the above-mentioned parameters including rate of energy consumption. To optimize the cluster heads, the required fitness function is evaluated by:

$$Fitness = \frac{1}{\theta R_{EC} + \rho\, SN_{ME} + \sigma\, D_{SN-BS}} \qquad (8)$$

To achieve potentially an optimal cost, the fitness function is minimized, furthermore every term in the fitness function is weighted based on its influence [16-21]. Hence, the fitness function is constrained by:

$$\theta + \rho + \sigma = 1 \qquad (9)$$

The proposed approach employs the abovementioned fitness function as the objective function utilized by GWO to optimize the cluster heads with minimum energy consumption and longer lifespan of the network. Accordingly, the current step can be considered as cornerstone to optimize the entire routing protocol in the next step.

III. GREY WOLF OPTIMIZER

Presently, metaheuristic optimization techniques are widely prevalent in various engineering fields as a result of their ability to address the local optima [32-35]. Grey wolves live in assemblies be composed of 12 wolves per assembly [36-37]. The social arrangement of wolves' society is presented in Figure 1; it comprises four classes as below:

a) Alpha wolves (α) are the chief of assembly and they have the highest power to issue instructions of hunting, sleeping in addition to other responsibilities.
b) Beta wolves (β) are the second class of society organization, they are an alpha`s associate in diverse organizational events.
c) The third class is Delta wolves (δ), they are directed by alphas and betas; nevertheless, they order the omega wolves. Detectives and raiders are the subclasses of this class.
d) Omega wolves (ω), are the forth class in the society organization, they are directed and instructed by other three classes.

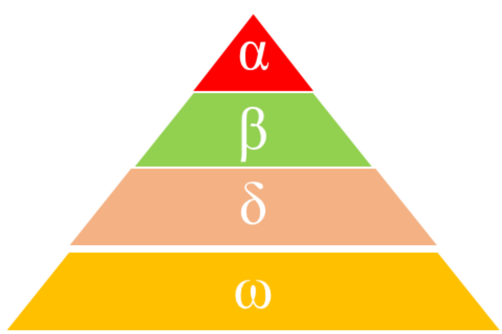

Figure 1. Classes of wolves' society

The hunting procedure is an exceptional social conduct of grey wolves, it includes different phases shown in Figure 2. These phases are as follows:

a) Chasing, and approaching the quarry.
b) Surrounding, and annoying the quarry until it stops.
c) Attacking the quarry.

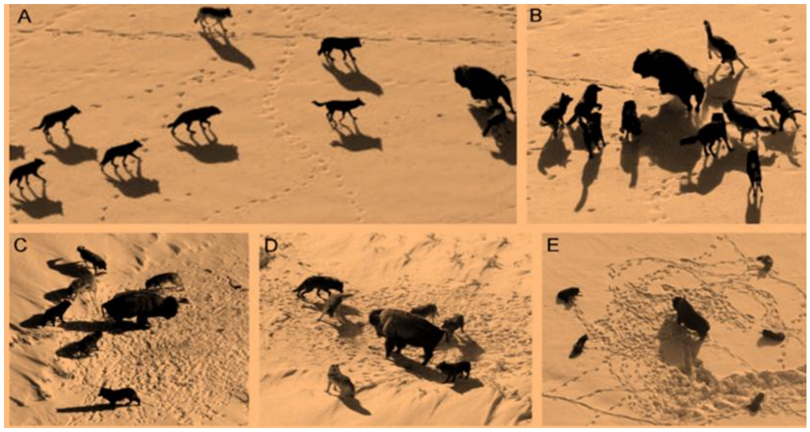

Figure 2. Hunting technique of grey wolves: (A) chasing and approaching, quarry (B-D) surrounding (E) attacking [36].

3.1 Mathematical Modeling

The mathematical model of GWO deliberates the rightest solution as the alpha (α). Therefore, the second and third superlative solutions are named beta (β) and delta (δ). The rest of the probable solutions are omega (ω).

3.1.1 Surrounding stage:

The surrounding way of grey wolves can be characterized by:

$$\vec{D} = | \vec{C} . \overrightarrow{X_q}(t) - \vec{X}(t)| \tag{10}$$
$$\overrightarrow{X_1}(t+1) = \overrightarrow{X_q}(t) - \vec{A}\ \vec{D} \tag{11}$$

Where D is the absolute value of distance between the best position of wolves and the quarry, *t* is the present iteration, *A* and *C* are coefficient vectors, $X_q(t)$ is the position vector of the quarry, and *X(t)* refers to the position vector of a grey wolf. *A* and *C* are computed by:

$$\vec{A} = 2\,\vec{a}\,\overrightarrow{r_1} - \vec{a} \tag{12}$$
$$\vec{C} = 2\,\overrightarrow{r_2} \tag{13}$$

The value of parameter *a* is a linearly reduced from 2 to 0 over iterations and r_1 and r_2 are random vectors in [0, 1].

3.1.2 Hunting stage:

Naturally, wolves can distinguish the location of quarries and surround them. However, at a certain search space there is no previous indication to determine the location of the optimal quarry [38]. Accordingly, the simulation of the hunting procedure initiates with an indispensable assumption that alpha (best candidate solution) beta, and delta have an adequate knowledge about the probable position of quarry. Subsequently, the other search agents including the omegas should update their locations in line with the location of the best search agent as illustrated in below:

$$\overrightarrow{D_\alpha} = | \overrightarrow{C_1} . \overrightarrow{X_\alpha} - \vec{X} | \tag{14}$$

$$\overrightarrow{D_\beta} = \left| \overrightarrow{C_2} . \overrightarrow{X_\beta} - \vec{X} \right| \tag{15}$$

$$\overrightarrow{D_\delta} = | \overrightarrow{C_3} . \overrightarrow{X_\delta} - \vec{X} | \tag{16}$$

$$\overrightarrow{X_1} = \overrightarrow{X_\alpha} - \overrightarrow{A_1}\ \overrightarrow{D_\alpha} \tag{17}$$

$$\overrightarrow{X_2} = \overrightarrow{X_\beta} - \overrightarrow{A_2}\,\overrightarrow{D_\beta} \tag{18}$$

$$\overrightarrow{X_3} = \overrightarrow{X_\delta} - \overrightarrow{A_3}\,\overrightarrow{D_\delta} \tag{19}$$

$$\vec{X}(t+1) = \frac{\overrightarrow{X_1} + \overrightarrow{X_2} + \overrightarrow{X_3}}{3} \tag{20}$$

As shown in Figure 3, the location of the quarry would be in an arbitrary place within a circle which is determined by the locations of commander wolves.

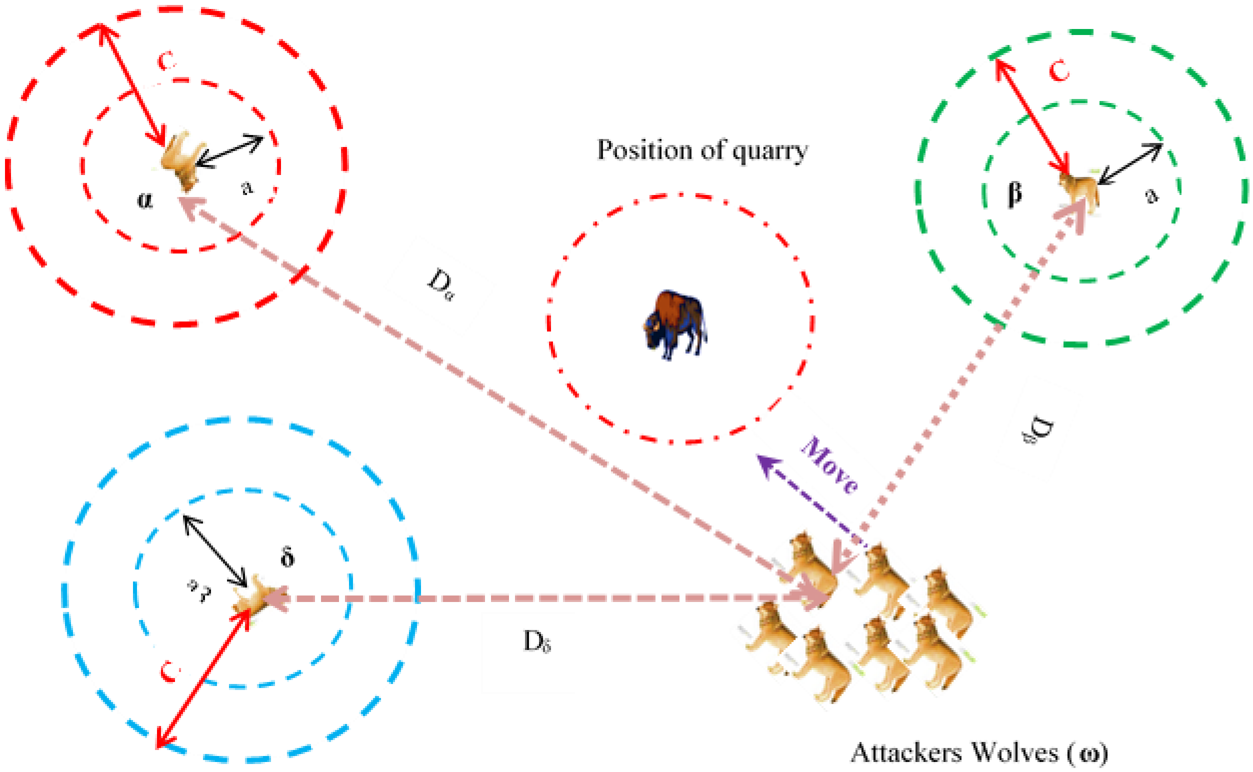

Figure 3. Updating positions of grey wolves considering the quarry's position.

3.1.3 Attacking quarry (exploitation):

The attacking stage is the final step implemented by wolves, as shown in Figure 4 , the grey wolves determine whether attack or move back according to the value of A which depends on a and r_1 as explained earlier in equation 12 while the value of C is evaluated by equation 13 based on r_2. Throughout the iterations of optimization process. Figure 4(a) shows that the quarry is attacked when $|A|$ less than 1.

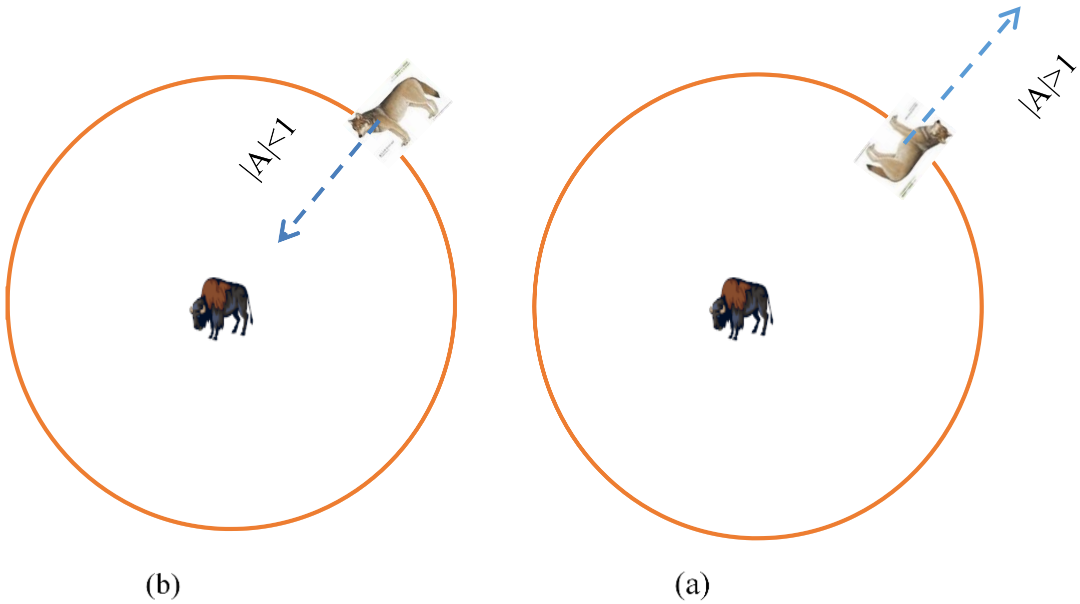

Figure 4. Attacking victim versus searching for quarry

3.1.4 Seeking quarry (exploration):

The wolves individually move to seek quarry and assemble to attack quarry. Figure 4 (b) also explains that when the value of $|A|$ is greater than 1 obligates the wolves to move away from the quarry to find a suitable quarry. As opposed to A, C is not linearly reduced to provide random values endlessly to underscore exploration throughout all iterations in optimization process. This randomization is significantly vigorous in addressing the local optima problem. The parameter C comprises random values in [0, 2] and provides arbitrary weights for quarry to probably underscore C is greater than 1 or C is less than 1 the impact of quarry in determining the distance in equation 15. The parameter a is decreased from 2 to 0 to update the value of A that signifies the basic factor for grey wolves to decide whether attacking the quarry or moving away.

3.2 Optimizing the cluster heads by GWO

In this study, GWO is utilized to determine the optimal cluster head node which is represented by the position of quarry in the GWO to minimize the objective function formulated in equation 9 .The whole algorithm of optimization process is shown in Figure 5 and summarized in the following:

a) Read the aggregate number of sensor nodes in the WSN.
b) Set the parameters of (GWO) including the size of population and the highest number of iterations
c) Initialize randomly the populations of wolves to minimize the objective function which is formulated in equation 9.
d) Update the positions of every wolves` class by using equation 20.
e) Check the present iteration number whether it is maximum or not to stop simulation.
f) Attain the minimum value of the objective function.

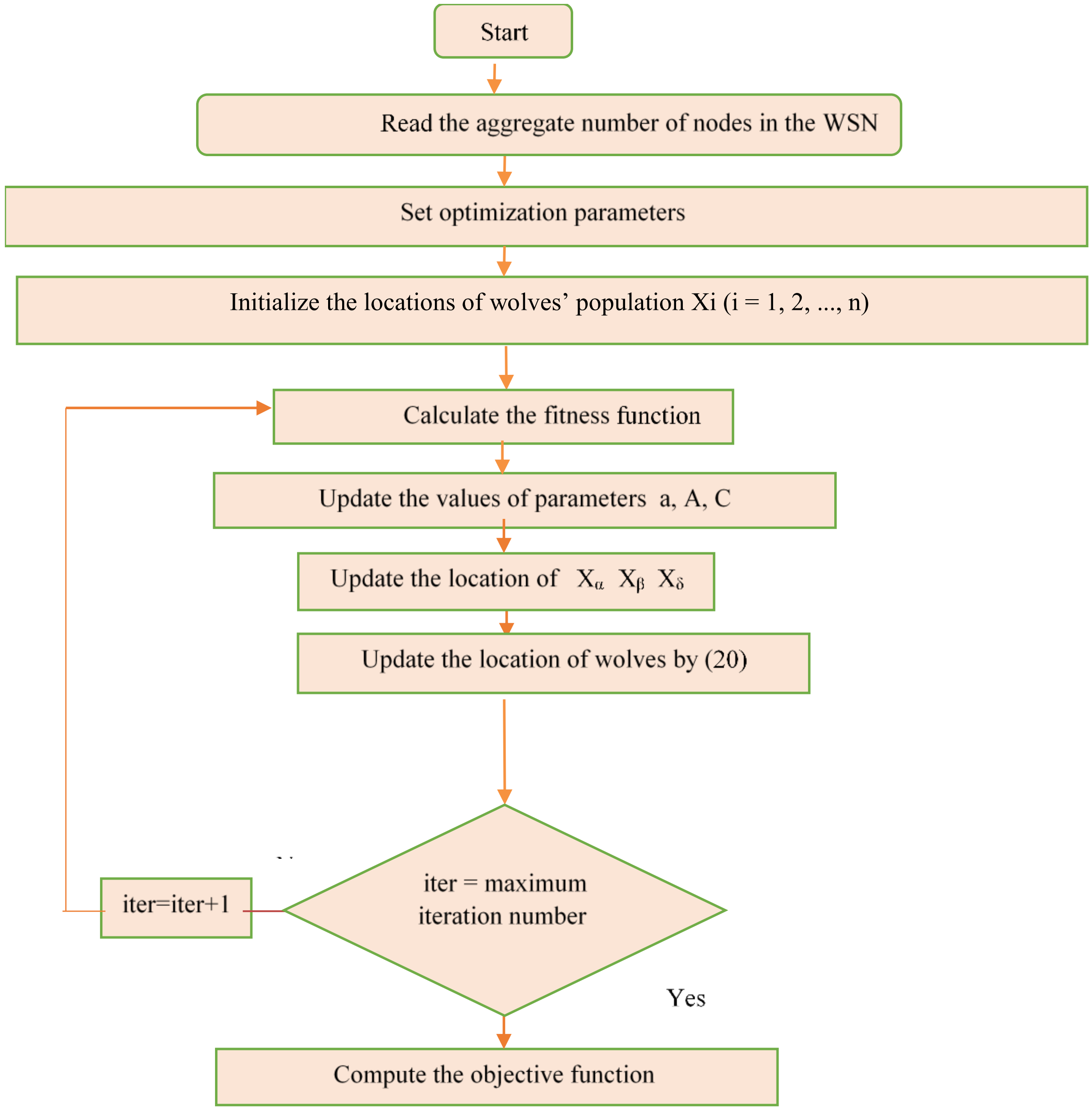

Figure 5. Whole algorithm of optimizing the cluster head based on GWO

To optimize a routing protocol, the data of all nodes are assembled and accumulated at the cluster head node which transmits data to the sink node while waiting for the all nodes installed in the WSN are shattered (dead). When the cluster head starts to receive data from other nodes that start to consume their energies. In this regard, the consecutive rounds of data transmission are not implemented unless the sensor nodes consume their energies and start to die. This process is consistently done to ensure that all nodes are dead. Therefore, the number of nodes in the WSN declines while the number of iterations rises. Furthermore, the stopping criteria of the algorithmic process of GWO will not rely on the number of iterations that is previously determined.

3.2 Sink Node Mobility

Indeed, the initial energies are exceedingly promising for optimizing the cluster head, since the lifespan of the WSN relies on the energy retained by the nodes. Consequently, the fundamental aim of the proposed approach is to integrate various crucial parameters that consume the existing energy of the nodes. As explain earlier, the main aim is to optimize the routing protocol, however in addition to the optimal cluster heads in the previous step, the sink mobility is a crucial factor in this challenge. Accordingly, in the proposed study also utilizes the algorithm of GWO to accomplish the sink mobility as explained below:

1. The total number of installed nodes (wolves) in the WSN is allocated the network parameters considered to optimize routing based on the sink mobility.
2. Similarly to the previous step that is related to optimizing the cluster heads, the whole algorithm of GWO is implemented however the fitness function is equation 5.

3. The sink mobility is optimized by mainly focusing on the cluster heads that are characterized by the least energy to protect the energy of these cluster heads since they have the extreme likelihood to decease. It is worth to mention that the above-mentioned fitness function is employed to distinguish the cluster heads that have least energy. The overall algorithm of optimizing the routing protocol is illustrated in Figure 6.

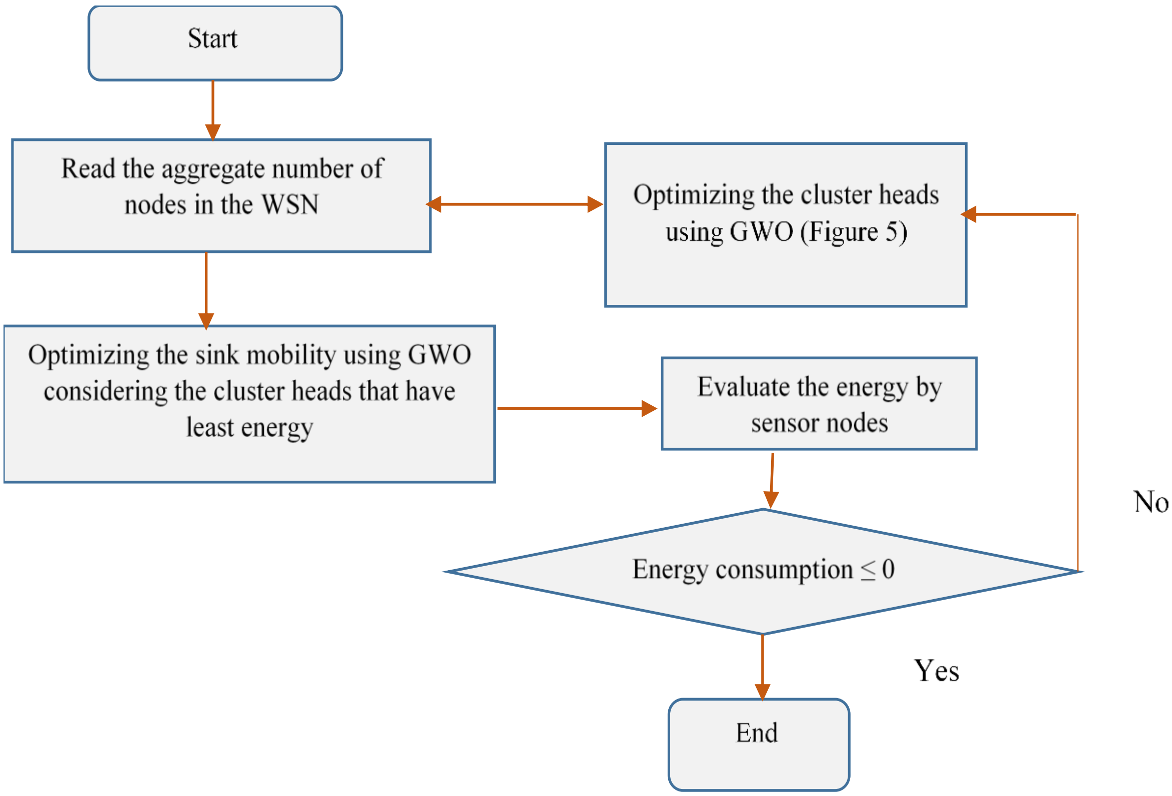

Figure 6. Overall algorithm of optimizing the routing protocol

IV. Results and Discussions

The simulation was conducted in Matlab R2021,the optimization parameters of GWO are 200 and 100 for maximum number of iterations and number of search agents respectively. To demonstrate the feasibility of the proposed approach compared to other methods, three methods including HGTO-MABA, TSBOA and MWCSGA were also simulated in this study. The total number of nodes were arbitrarily installed with characterizing a number of nodes as cluster heads in the WSN. In the execution, 700 sensor nodes were utilized and scattered over the sensing area, while the base station positioned at (100,100). The computational parameters are illustrated in Table 1.

Table 1. Computational parameters

Number of sensor nodes	700
sensing area	300 × 300 m^2
Position of sensor nodes	(100,100)
control packet capacity	300
data packet capacity	5000
Primary energy of nodes	0.75 joules

4.1 Performance Evaluation based on a various number of Implementation Rounds

In this part of simulation, the performance of proposed GWO was compared to HGTO-MABA, TSBOA and MWCSGA schemes considering the variation of number of implementation rounds from 0 to 5000. A number of the evaluation measures were utilized including number of alive nodes, mean throughput and number of dead nodes. The number of alive nodes is presented in Figure 7, the performance of the GWO outperforms the feasibility of HGTO-MABA, TSBOA and MWCSGA. After 4500 rounds, the all nodes (700) are still survived with GWO, while with other methodologies they do not exceed 110 nodes.

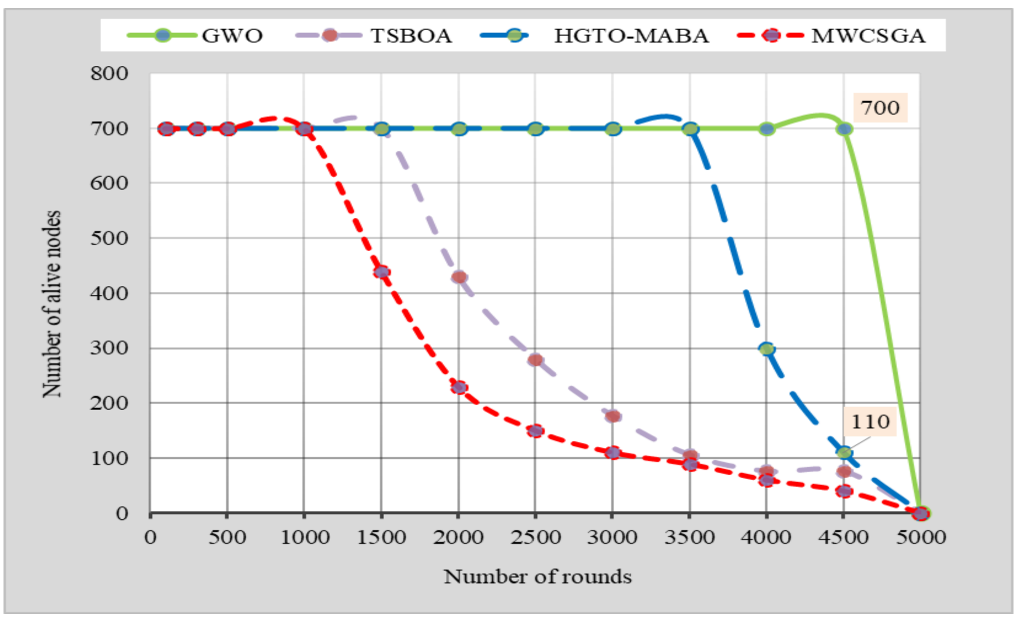

Figure 7. Number of alive nodes during implementation

The attained results of throughput are shown in Figure 8, the responses curves demonstrate the viability of GWO compared to the other three schemes. After 4500 rounds, the throughput with the proposed approach stays above 1000 (bit/sec), in contrast, the throughput extremely declined to 176 (bit/sec) as it is occurred with MWCSGA. It is worth to mentioning that the significant improvement which is accomplished in the throughput results comes from considering distances between nodes in the proposed fitness function. Hence, the declining of packets by the unsuitable nodes are fully avoided.

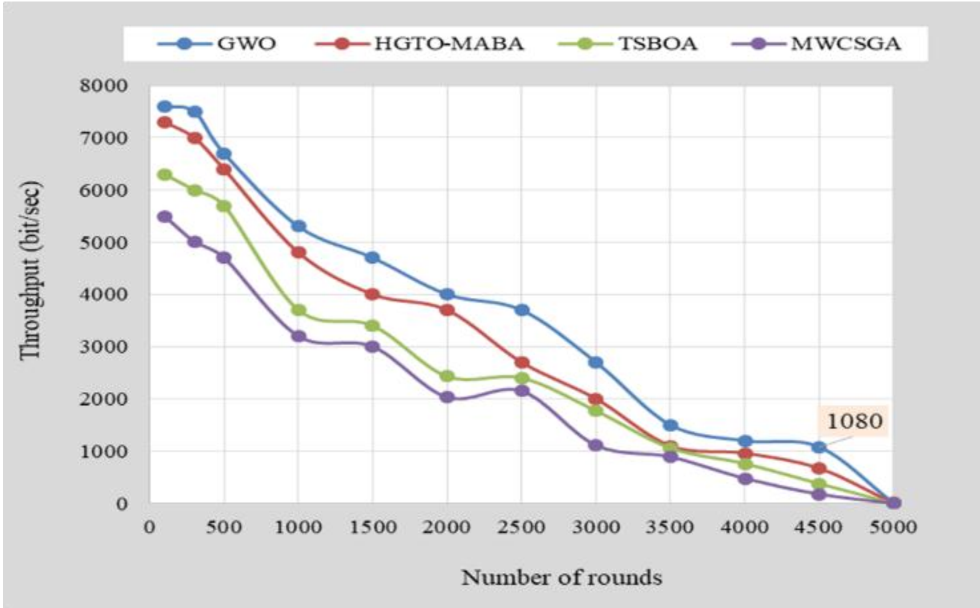

Figure 8. Throughput during implementation.

Figure 9 clearly illustrates that the number of dead nodes after 1500 rounds with the proposed approach is still 0, conversely with the other three methodologies it abruptly increases to exceed 200 nodes as it is occurred with MWCSGA . It is worth to mention that the optimizing algorithm of cluster heads which are determined by the GWO is an effective factor to curb the early death of nodes in this study.

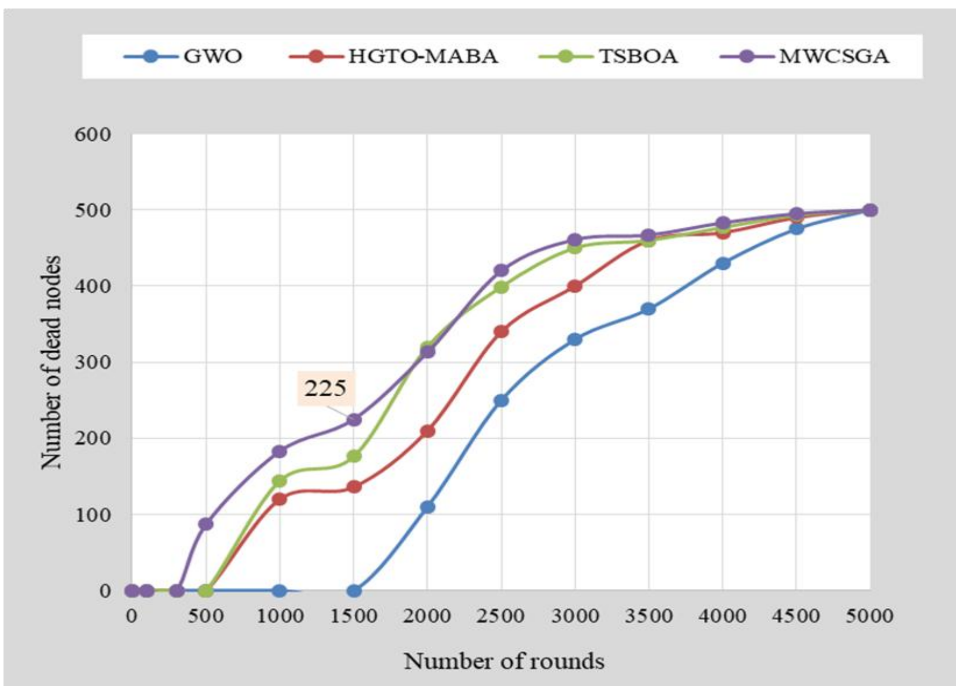

Figure 9. Number of dead nodes during implementation.

4.2 Performance Evaluation considering a diverse quantity of nodes

In this part of simulation, a comparative study between the proposed approach and other three methods was conducted considering the variation of number of sensor nodes from 0 to 700. A number of the evaluation measures were utilized including packet delivery ratio, probability of avoiding unsuitable cluster heads, energy consumption, and computation cost. The attained results of the packet delivery ratio are shown in Figure 10which obviously verifies that the packet ratio with GWO is consistently higher than those obtained by other schemes. The higher minimum value of the packet delivery ratio is 68% accomplished by the proposed approach.

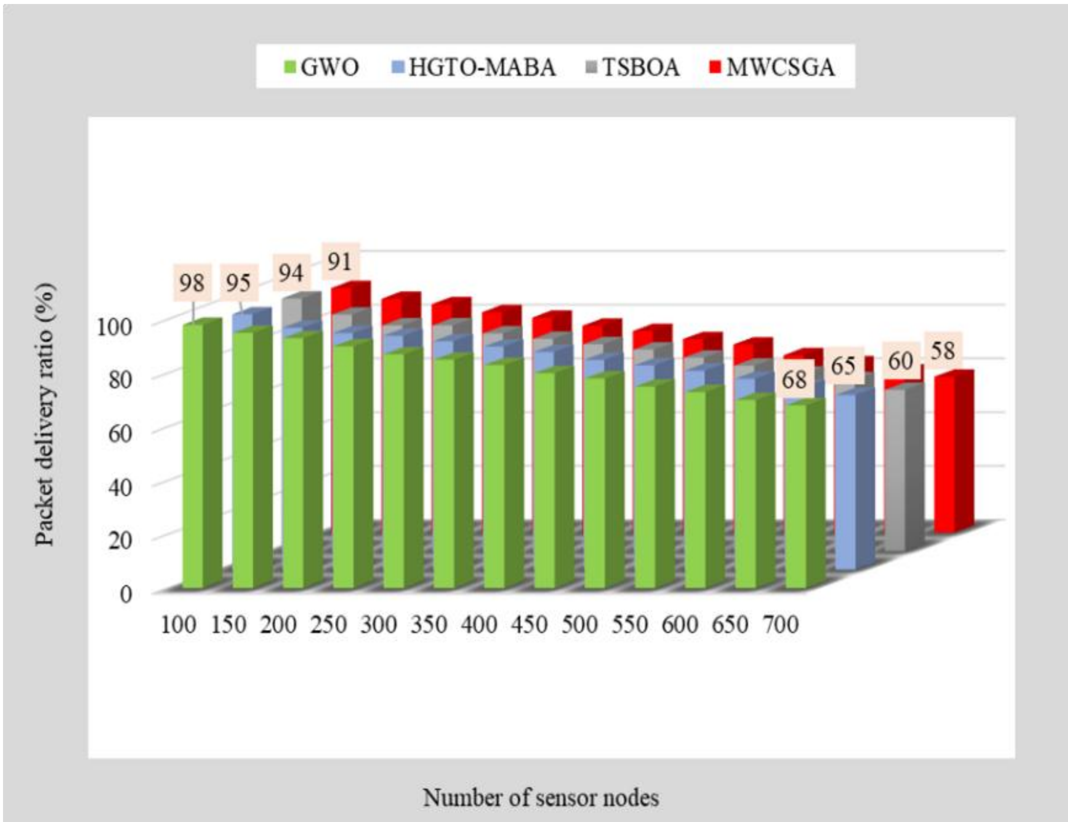

Figure 10. Packet delivery ratio during implementation

The results of probability of avoiding unsuitable cluster heads are shown in Figure 11 which demonstrates that the proposed approach is adequately robust to optimize the most appropriate cluster heads nodes and avoid optimizing the unsuitable nodes as cluster heads. The proposed approach steadily achieves higher probability compared to HGTO-MABA, TSBOA and MWCSGA.

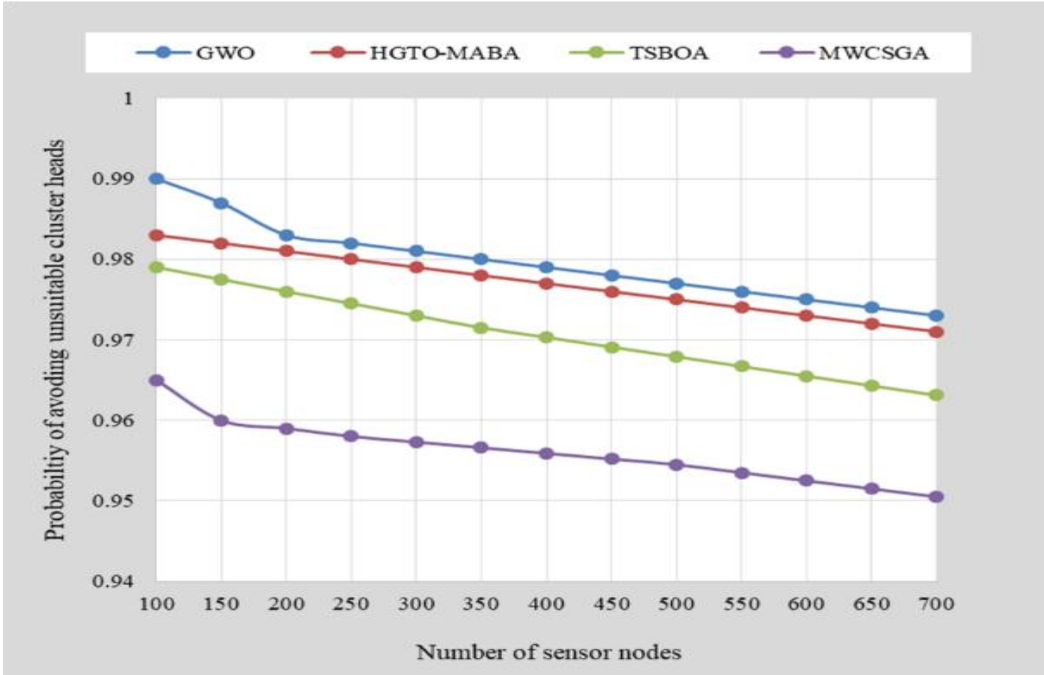

Figure 11. Probability of avoiding unsuitable cluster heads during implementation

The attained results of energy consumption are illustrated in Figure12 which demonstrates the economic feasibility of GWO compared to other schemes. The energy consumption of nodes attained by the GWO is the lowest and not exceeds 200 Joule while there is a remarkable increase in the energy consumption attained by other methods and it may reach to 287 Joule as it is occurred with MWCSGA.

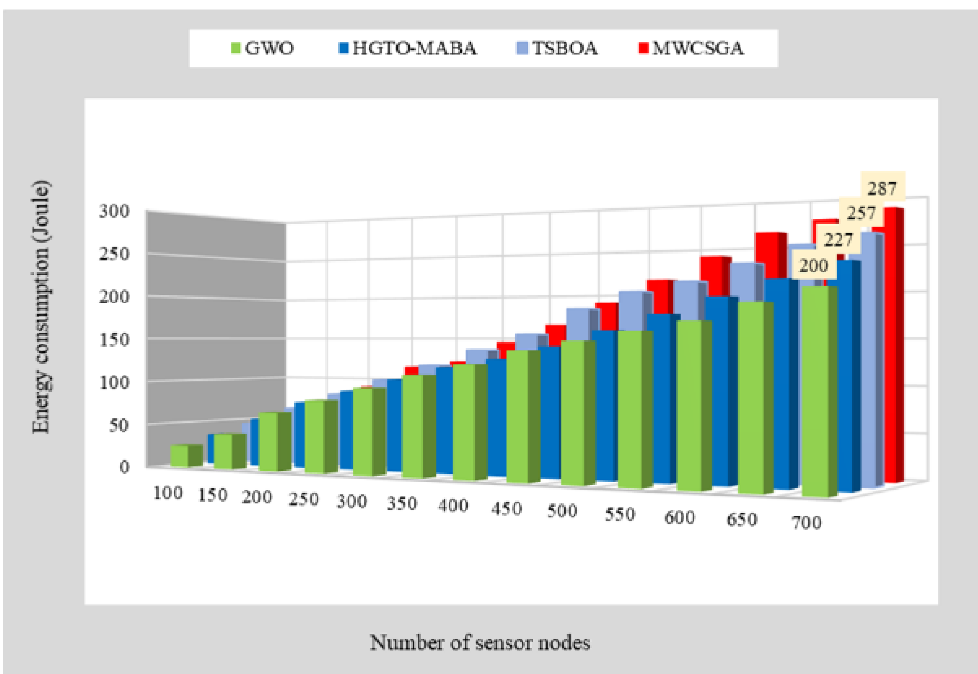

Figure 12. Energy consumption during implementation

Figure 13 exceedingly demonstrates that the proposed approach is an efficient adequately to address the computational cost that represents one of key shortcomings in the previous literature. The computational cost with the GWO enormously and consistently declines to 30.5% compared to 39.6%, 45.5% and 49.5% achieved by HGTO-MABA, TSBOA and MWCSGA respectively.

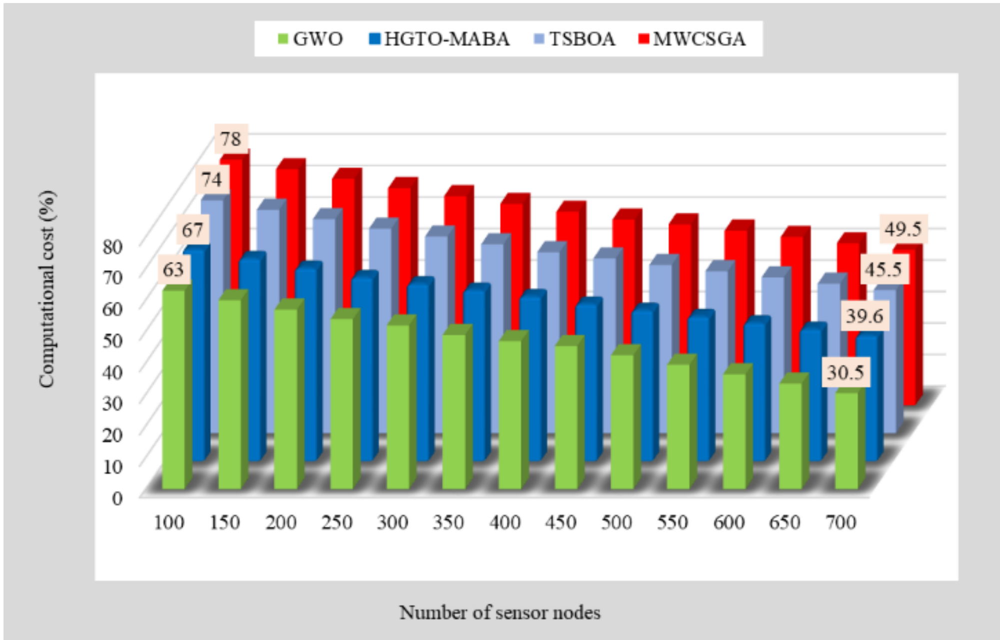

Figure 13. Computational cost during implementation

V. Conclusion

The proposed research investigated the performance of the optimal routing protocol in the Wireless Sensor Network (WSN) based on the Grey Wolf Optimizer. The optimizer was employed to determine the optimal cluster head nodes. Unlike many previous studies, this research also optimized the sink mobility to protect the energy of cluster heads, which are at significant risk of depletion, thereby prolonging the lifespan of the WSN. Various evaluation measures were utilized to prove the feasibility of the proposed approach compared to other schemes. Overall, the research findings highlight the effectiveness of the proposed routing protocol with the Grey Wolf Optimizer in augmenting the performance and longevity of the WSN. The consideration of multiple factors, such as energy consumption, node locality, and sink mobility, contributes to more efficient cluster head node selection. As a result, the WSN can operate more effectively and extend its operational life. Further research can explore additional optimization techniques and investigate the scalability of the proposed approach to larger WSN deployments. Additionally, conducting real-world experiments and performance analysis under varying environmental conditions will be valuable in validating the findings and ensuring the practical applicability of the proposed protocol.

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