




Article

Multi-Objective Energy Efficient Adaptive Whale Optimization Based Routing for Wireless Sensor Network

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Abstract: In Wireless Sensor Networks (WSNs), routing algorithms can provide energy efficiency. However, due to unbalanced energy consumption for all nodes, the network lifetime is still prone to degradation. Hence, energy efficient routing was developed in this article by selecting cluster heads (CH) with the help of adaptive whale optimization (AWOA) which was used to reduce time-consumption delays. The multi-objective function was developed for CH selection. The clusters were then created using the distance function. After establishing groupings, the supercluster head (SCH) was selected using the benefit of a fuzzy inference system (FIS) which was used to collect data for all CHs and send them to the base station (BS). Finally, for the data-transfer procedure, hop count routing was used. An Oppositional-based Whale optimization algorithm (OWOA) was developed for multi-constrained QoS routing with the help of AWOA. The performance of the proposed OWOA methodology was analyzed according to the following metrics: delay, delivery ratio, energy, NLT, and throughput and compared with conventional techniques such as particle swarm optimization, genetic algorithm, and Whale optimization algorithm.

Keywords: clustering; whale optimization; supercluster head (sch); hop count; routing; Wireless Sensor Networks (WSNs); fuzzy inference system (FIS)



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1. Introduction

WSNs cooperatively screen, detect, and gather data of fluctuated conditions or screen objects continuously through different styles of incorporated small-scale sensors [1]. Remote gadget hubs are input gadgets that detect different physical conditions such as temperature, pressure, sound, wetness, and so forth. WSNs are widely utilized in numerous natural applications, military applications, and canny vehicle systems [2]. The liberated hub sends the apparent information to the peak design descended gadget for investigation. The essential test of a WSN is to identify bunches of the most extreme sum as the potential vitality devoured by gadget hubs and to ensure ideal execution for clients [3]. Each gadget has the fitness to move and receive parcels from elective hubs, presenting advantages in terms of its difference in access [4]. Advances in remote correspondence make it possible to create WSNs comprising modest gadgets that gather information by collaboration [5].

There are a few issues in terms of sensor arrangement, such as adjusting or stimulating the hub batteries in light of specially appointed activity in basic conditions because of the imperceptible nature of WSNs [6]. The primary utilization of WSNs includes healthcare checks, area observation, environmental/earth detection, air tainting inspections, forest fire area, landslide revelation, water quality checks, natural calamity neutralizing activity, industrial observations, machine wellbeing observations, data logging, water/wastewater checks, structural wellbeing observations, etc. [7].

The prevalence and relevance of remote innovation have led to requests for higher limits, availability, and QoS, which would enhance the attractiveness of current WSNs [8]. WSNs should be remote systems made out of an exceptionally large number of interconnected hubs which sense an assortment of information, speak with one another and possess calculation abilities. QoS conventions can be executed in Wireless Local Area Networks (WLAN) with some alteration in light of the fact that the last jump is the main remote stage in these systems [9]. Along these lines, the Whale Optimization Algorithm (WOA) was utilized to improve vitality effectiveness and QoS in WSNs [10]. An Oppositional-based Whale optimization algorithm (OWOA) was developed for multi-constrained QoS routing with the help of AWOA. The performance of the proposed OWOA methodology was analyzed according to the following metrics: delay, delivery ratio, energy, NLT, and throughput and compared with conventional techniques such as Particle swarm optimization (PSO), Genetic algorithm (GA), and WOA.

The key objective of the proposed methodology was to improve energy-effective routing in WSN. To avoid time consumption and energy consumption, CH was elected with the help of OWOA. Then, to further develop the presentation of the scheme, SCH was selected. For this communication, an effective course dependent on the bounce tally of the sensor hubs was set up. The article is organized as follows: in Section 2, a literature survey is analyzed, followed by a detailed discussion of the proposed technique in Section 3. The test results are analyzed in Section 4 and the results are presented in Section 5.

2. Literature Review

Researchers have produced plenty of research on routing in WSNs; some of the research is analyzed here. Nikolov, M. et al. (2018) [11] presented encoded detection for communitarian encoding and the transmission of sensor information that lessens correspondence. Encoded detection spared 80% of the vitality of an ideal hypothetical transmission circulated shaft shaping design. He demonstrated that re-creation and hypothetical deductions could be achieved as the size of a hub bunch develops the exhibition of encoded detection which provides the ideal transmission vitality productivity. Singh, R. et al. (2017) [12] broke down WSNs as designated systems used for a wide range of current requirements such as observation, following, process control, and so on. Physical information viz. temperature, pressure, humidity, and more was spread out into the system for further preparation. The technique was accomplished with good results over the system. Brar, G. S. et al. (2016) [13] analyzed energy consumption in WSNs. They developed several routing protocols to improve the presentation of the system. Of those algorithms, the DSR protocol was the most appropriate as it had a small energy density. The performance analysis, compared with the hybrid access of the planned routing protocol, provided the best result with a low bit error rate, low latency, and low power consumption. Kumar, S. et al. (2019) [14] introduced multi-channel DTMA scheduling algorithms aimed at reducing total energy utilization in the system. The planned algorithms were used to effectively plan multiple radio channels while eliminating conflicts. The algorithm reduced the consumption of energy in every timeslot when excluding a certain timeslot. In the simulation results, the algorithm reduced the computation time. Zhang, W. et al. (2017) [15] broke down another bunching calculation in WSNs. An E2HRC steering convention for remote sensor systems was planned by directing calculations and using support strategies. The exploratory results indicated that in the examination against the first RPL, the E2HRC steering convention more successfully adjusted WSN vitality utilization, and in this way diminished both hub

vitality utilization and the number of control messages. Zhang, W. et al. (2018) [16] developed a network layer in the WSN. Using CLO classical, a vitality proficient ring cross-layer enhancement calculation was proposed and another steering calculation called Leach-CLO was likewise proposed for a ring-checking space. This Leach-CLO-directing calculation depended on a standard Leach calculation. The examination results indicated that this directing calculation could successfully and effectively balance the vitality utilization in remote sensor systems. Ahmed, E. F. et al. (2019) [17] presented a vitality effective bunching and various-leveled directing calculation method named the Energy-Efficient Scalable Routing Algorithm (EESRA). EESRA utilizes multi-jump transmissions for intra-bunch correspondence to execute a crossover WSN MAC convention. The reproduction result demonstrated that EESRA improved on the benchmarked conventions in terms of the burden of adjusting and vitality productivity on large scale WSNs. Ezdiani, S. et al. (2017) [18] developed an adaptable framework that responded to the dynamic changes in procedure requests. Physically organized execution could be anticipated by dissecting the authentic information out of sight on a system test or system virtual arrangement. The experimentation and appropriateness of client-driven QoS models on the framework were reported. Energy consumption is the biggest issue in Wireless Sensor Networks (WSNs) due to the limited energy resources of the sensor nodes. In order to overcome the energy consumption and network lifetime bottlenecks, Anees, J. et al. (2020) [19] proposed Hesitant Fuzzy Entropy-based Opportunistic Clustering and a data-fusion technique. An opportunistic link between sensor nodes in heterogeneous clustering could be made by taking advantage of the asynchronous working–sleeping cycle of sensor nodes. The optimal power flow is a pressing operational issue with multiple technical and financial facets with regard to environmental considerations. For the purpose of solving single-objective optimal power flow as well as multi-objective frameworks, Dabah, M. E. et al., (2022) [20] suggested a multiple-objective optimizer called the non-dominated sorting whale optimization algorithm. The optimal power flow can be created with a range of technical and financial power system objectives. Boursianis, A. D. et al. (2021) [21] proposed an intelligent irrigation system. The platform's IoT node functions are explained in detail. The RF energy harvesting method was used to provide power to the platform's IoT. A rectenna module for the capture of radiofrequency radiation was designed. The built rectenna performed satisfactorily as a harvester of ambient sources in an outdoor setting.

3. Energy Efficient Data Transmission in WSN

The main objective of the proposed methodology was to provide energy efficient information transformation in WSNs utilizing multiple stages. The planned methodology of the block diagram is presented in Figure 1. In this paper, initially, CH was selected with the help of AWOA. In this algorithm, based on the average cluster reserve with the remaining drive, the optimal CHs were selected. The selected CHs received information from the specific non-cluster head successfully, with which we reduced the time and traffic congestion. Then, to achieve the minimum delay and energy consumption, the SCH was selected from the elected grouping CHs utilizing the FIS. Then, SCHs collected the information from CHs and forwarded it to the BS.

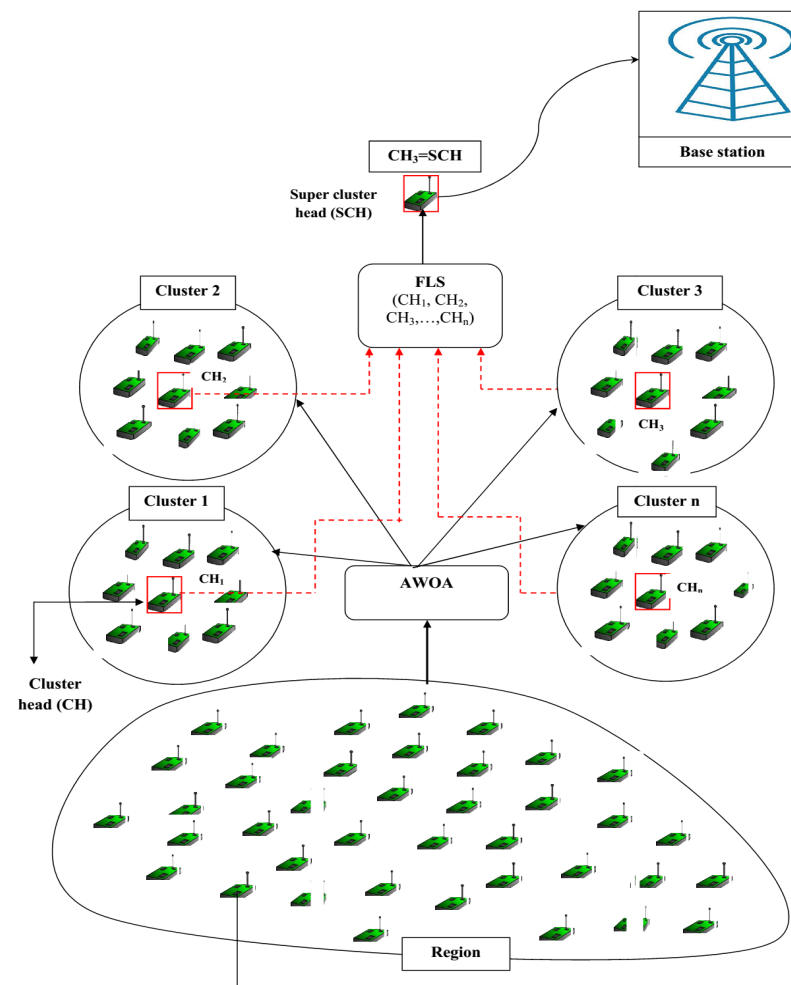


Figure 1. Proposed data transmission in WSN.

3.1. Difference between WOA and Our Proposed Model

An Oppositional-based Whale optimization algorithm (OWOA) was developed for multi-constrained QoS routing with the help of AWOA. The social behavior of humpback whales is imitated by the Whale Optimization algorithm. The three fundamental ideas behind the whale optimization algorithm are searching for prey, encircling prey, and using a bubble-net attack. These phases are used by WOA to determine the best solutions. Opposition-based learning (OBL) is used in the evolution phase of WOA to increase the convergence rate. The basic goal of OBL is to identify a better candidate solution while taking into account both an estimate and its inverse estimate, or a guess and the opposite guess, which is closer to the overall optimum [22]. By using quasi-oppositional-based learning (QOBL), the effectiveness and elegance of the solution increased.

3.2. Cluster Head Selection Using AWOA

Consider the geographical area and number of sensors. The sensor is used to collect information surrounding the position and transmit the information to BS. To decrease energy consumption, time, and avoid failure nodes, the grouping heads are selected through the service of AWOA. AWOA is a combination of WOA and quasi-oppositional-based learning (QOBL). This algorithm creates its population arbitrarily through the investigation with a manipulation stage that can create a suitable solution due to investigations about home ideals. To speed up convergence and enhance the quality of the solution, the quasi-opposition (QOBL) based learning mechanism was adopted for the WOA. The CH generating technique is discussed in detail in the following sections.

3.2.1. Encoding the Solution

The number of sensor nodes and the parameter used in AWOA are initially set. With the population number N , the positions of whales are then initialized. To begin with, the CHs are chosen at random. The solution for encryption evaluation is given in Equation (1).

$$S_i = [s_1(t), s_2(t), \dots, s_i(t)] \quad (1)$$

where $s_i(t)$ denotes the position of the i th Whale or CH.

3.2.2. Create Quasi-Oppositional Solution

After the solution initialization, to increase the searching ability, a quasi-oppositional solution is created. This solution is used to reduce the computation time, as well as enhance the convergence abilities of the WOA.

The opposite solution S_0 to any arbitrary solution $S \in [u, v]$ can be represented as follows:

$$S_0 = u + v - S \quad (2)$$

Multi-dimensional search space (d -dimensions), which is shown in Equation (2), is written as follows:

$$S_0^i = u^i + v^i - S^i; i = 1, 2, \dots, d \quad (3)$$

For any arbitrary solution $S \in [u, v]$, its quasi-opposite solution S_{q0} can be written as follows:

$$S_{q0} = rand\left(\frac{u + v}{2}, S_0\right) \quad (4)$$

Multi-dimensional search space (d -dimensions) can be written as follows:

$$S_{q0}^1 = rand\left(\frac{u^i + v^i}{2}, S_0^i\right) \quad (5)$$

3.2.3. Fitness Calculation

During the encryption procedure, the fitness of every whale is calculated. Fitness is defined based on standard deviation (SD) and average distance. The fitness function can be written as follows:

$$Fitness = \frac{1}{A_{Dist}} \times \frac{1}{\sigma} \quad (6)$$

where,

$A_{Dist} \rightarrow$ Average distance between CH and SN

$\sigma \rightarrow$ SD

Based on the above fitness function, all SNs should be assigned to their closest CH. The A_{Dist} is calculated using Equation (7).

$$A_{v}Dist = \frac{1}{n} \sum_{i=1}^n D_i \quad (7)$$

where,

$n \rightarrow$ Number of SN

$D_i \rightarrow$ Distance between SN and CH.

The SD is designed based on the ratio of residual energy and the number of the member SNs of a CH if the gateway G_i has N_i number of member SNs and residual energy $E_{Residual}(G_i)$. The shorter the SD, the higher the fitness value [23]. Then, the SD can be calculated follows:

$$\sigma = \sqrt{\frac{1}{m} \sum_{i=1}^m (\mu - R_i)^2} \quad (8)$$

$$\mu = \frac{1}{m} \sum_{i=1}^m R_i \quad (9)$$

$$R_i = \frac{E_{Residual}(G_i)}{n_i} \quad (10)$$

where,

$m \rightarrow$ Number of CHs

3.2.4. Update the Position of the Current CH

To update the location of the CH, the following operations are used.

Encircling Prey

In this section, the whale will find the prey and will suddenly encircle the prey. Based on prey, other whales also update their status quo. The update function is given as follows:

$$\vec{U} = \left| \vec{S} \cdot w^{best}(k) - w(k) \right| \quad (11)$$

$$w(k+1) = w^{best}(k) - \vec{B} \cdot \vec{U} \quad (12)$$

where,

$k \rightarrow$ Present iteration

$\vec{B}, \vec{S} \rightarrow$ Coefficient vector

$w^{best} \rightarrow$ Best solution,

$w \rightarrow$ Vector of the current position,

$\| \rightarrow$ Absolute value

Equations (13) and (14) can be used to calculate the coefficient vectors and are as follows:

$$\vec{B} = 2\vec{b} \cdot \vec{r} - \vec{b} \quad (13)$$

$$\vec{S} = 2 \cdot \vec{r} \quad (14)$$

where b is the linear reduction in iterations from 2 to 0 during both the exploration and exploitation stages. $r \in (0, 1)$.

Bubble-Net Attacking Method

Two methodologies, namely the Shrinking circling component and Spiral refreshing position are used to numerically shape the air pocket net conduct of humpback whales as discussed below [24].

Shrinking Encircling Mechanism

The value b in Equation (13) should be decreased from 2 to 0 to attain the behavior and \vec{b} is also used to decrease the value of \vec{B} . Here, \vec{B} varies from $[-b, b]$. The updated position of the search agent is defined somewhere for $\vec{B} \in [-1, 1]$.

Spiral Updating Position

A spiral update can be calculated between the position of a whale with prey. The update function can be written as follows:

$$w(k+1) = D \cdot e^{bt} \cdot \cos(2\pi t) + w^{best}(k) \quad (15)$$

$$D = \left| w^{best}(k) - w(k) \right| \quad (16)$$

During optimization, the whale's position is updated by selecting a spin model with a 50% probability, or by optimizing the mechanism around this simultaneous behavior. The update function is given in Equation (17).

$$w(k+1) = \begin{cases} w^*(i) - \vec{A} \cdot \vec{U} & \text{if } R < 0.5 \\ D \cdot e^{bt} \cdot \cos(2\pi t) + w^{best}(k) & \text{if } R \geq 0.5 \end{cases} \quad (17)$$

Here, $R \in [0, 1]$. The humpback whales build a bubble net by searching for prey at random.

Searching for Prey (Exploration Phase)

The difference of the \vec{A} vector can be used in the same way to search for prey. They are searching for each other's humpback whales at random. As a result, random values of \vec{A} of greater than or less than 1 are used to motivate the examined representative to move away from the situation whale. During the exploitation phase, the state of the search agents is updated. The OWOA algorithm permits this methodology and $|\vec{A}| > 1$ is the focus of the study to accomplish a comprehensive examination. The calculated prototypical case is presented below:

$$\vec{U} = \left| \vec{C} \cdot w_{rand} - w \right| \quad (18)$$

$$w(k+1) = w_{rand} - \vec{A} \cdot \vec{U} \quad (19)$$

Termination criteria are as follows: The AWOA algorithm is eliminated since the best CHs are obtained for the satisfaction of a termination criterion. Based on the CH, the nearest SN nodes are formed to obtain a cluster [25].

3.3. Super Cluster Head Selection

After the CH selection process, a super grouping head is elected since the selected CHs can maximize the network lifetime and energy efficiency. All CHs and SCHs are used to collect information from and forwarded to BS. In this paper, FIS is used for the SCH selection process. To control the consumption of energy and raise the lifetime of an SN for data transmission, the optimal CH is calculated. In this process, initially, the nodes in the WSN are tested by fuzzy blocks to determine the best nodes in each region, as a cluster leadership candidate. Each node in the WSN calculates the power of the node, the concentration of the node, and the center of the node. These values are given as inputs to the Fuzzy Logic System (FLS).

FLS has four major mechanisms, namely fuzzy inference, fuzzy rules, fuzzy machine, and diffuser. Blurry changes are input into a fuzzy set of related entries. The fuzzy rule database encloses different fuzzy inference comments that perform in the IF-THEN arrangement. The fuzzy inference machine first calculates the fuzzy degrees of each fuzzy rule. Then, it creates vague conclusions from every ambiguous rule. The defuzzifier produces the output which changes the fuzzy value above into a smooth value using the gravity mode or centroid mode. MF is a curve in which every point in the information universe is translated to a member value between 0 and 1. Here, the degree of ambiguity in membership is determined using member functions (MFs), such as trapezoidal and triangular. The "min" function is utilized for the "and" operator in this manner, the "max" function is used for the "or" operator, and the centroid failure is used for the process [26]. The fuzzy structure is given in Figure 2.

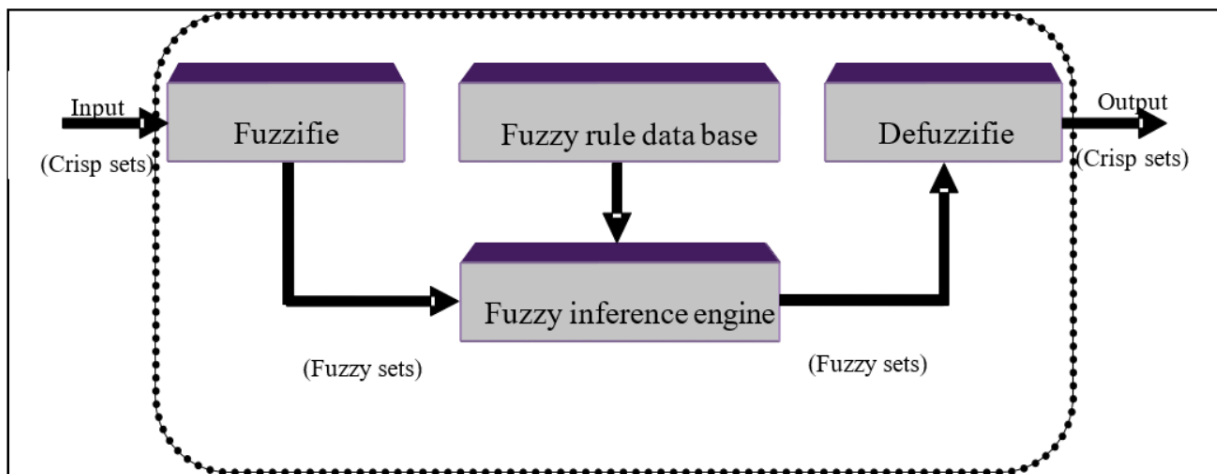


Figure 2. Fuzzy logic system.

For fuzzy rule generation, every node of WSN computes descriptors such as the energy of the hub and local reserve of the node with the centralization of the node. The energy, concentration, and centrality are given as the inputs of the fuzzy system. Concerning the energy of the node, the acceptable energy level of the cluster node is elected for the grouping head. In this process, all the nodes know their used energy and the remaining energy. Here, each node that transmits K bit data to a distance is used in the same way as S energy, which is achieved from the equation.

$$E_s(K, d) = E_{elec} \times K \times \varepsilon_{amp} \times K \times d^2 \quad (20)$$

The energy for receiving the k bit is calculated using the equation below.

$$E_R(K) = E_{elec} \times K \quad (21)$$

In the above equation, d is a constant that is associated with the distance between two hubs. E_{elec} and ε_{amp} are constant values which are given in the equation below.

$$\varepsilon_{amp} = 100 \text{ pJ/bit/m}^2 \quad (22)$$

$$E_{elec} = 50 \text{ nJ/bit} \quad (23)$$

Centralization of the node (NC):

If the value of centrality is low, it means a lower amount of energy is required for transmitting data [27]. NC is calculated using the equation below.

$$NC = \frac{\sqrt{U}}{NZ} \quad (24)$$

where, $U = \sum_{j \in M(i)} \frac{d^2(i, j)}{|M_i|}$, d denotes the distance between the grouping head and the hub, $|M_i|$ represents the number of neighbors of node I and NZ is the size of the sensing area.

The local distance of the node:

The distance connecting the center hub with its neighbor is calculated. Figure 3 demonstrates the center node (C) and its neighbors within the r radius. The local distance of each node is calculated with the help of the equation below.

$$LD = \sum_{i=1}^n D_i \quad (25)$$

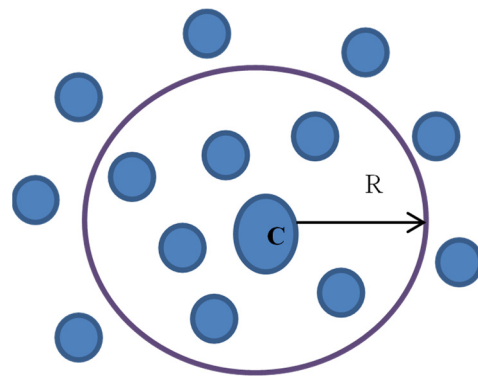


Figure 3. Local distance of node calculation.

After the input of the fuzzy system calculation, the inputs are transferred to FLS. The fuzzy system's step-by-step procedure is described below.

Step 1: Discretization:

The acceptable energy level of the cluster node is selected for the cluster head. In this process, all the nodes know their used energy and the remaining energy. Here, each node that transmits K bit data to a distance is used in the same way as S energy, which is achieved from the equation below.

$$\text{linguistic value} = \begin{cases} L0 < (E, Con, Cen) < 0.25 \\ M0.25 \leq (E, Con, Cen) < 0.75 \\ H(E, Con, Cen) \geq 0.75 \end{cases} \quad (26)$$

The linguistic variables for Energy, Concentration, and Centralization are defined based on the equations given below.

$$\text{Energy} = \{\text{low, medium, high}\} \quad (27)$$

$$\text{Concentration} = \{\text{low, medium, high}\} \quad (28)$$

$$\text{Centrality} = \{\text{close, adequate, far}\} \quad (29)$$

Step 2: Rule generation process:

After the calculation of linguistic variables, rules are created. In this chapter, seven classifications are available, namely V_{small} , small, r_{small} , medium, r_{large} , large and V_{large} . A total of $3 \times 3 \times 3 = 27$ rules are produced based on the fuzzy input and output. Table 1 shows the fuzzy rules that were used.

Table 1. Fuzzy rules used.

Rule No.	Variables for Input			Output
	Energy	Concentration	Centrality	Chance
I	H	L	H	VH
II	H	L	I	VH
III	H	L	L	H
IV	H	I	H	H
V	H	I	I	H
VI	H	I	L	I
VII	H	H	H	I
VIII	H	H	I	I
IX	H	H	L	L
X	I	L	H	I
XI	I	L	I	L
XII	I	L	L	L
XIII	I	I	H	I
XIV	I	I	I	I
XV	I	I	L	L
XVI	I	H	H	I
XVII	I	H	I	L
XVIII	I	H	L	VL
XIX	L	L	H	H
XX	L	L	I	I
XXI	L	L	L	L
XXII	L	I	H	I
XXIII	L	I	I	L
XXIV	L	I	L	VL
XXV	H	H	H	L
XXVI	H	H	I	VL
XXVII	L	H	L	VL

Where L = Low, H = High, I = Intermediate, VL = Very low, and VH = Very High.

Step 3: Membership Function:

The membership function is proposed by selecting the correct membership function. In this work, the triangular membership occupation was utilized. The membership function is used to convert the value into a fuzzifier value. The membership occupation consists of three variables, viz i , j and k . Here, i represents the lower boundary value, j represents the upper bound value and k represents the center value. The characteristics of the membership function are given below.

- The MF completely describes the fuzzy set;
- A, MF offers a quantity of the degree of resemblance of a component to a fuzzy set;
- MF can take any shape; however, some general examples become visible in real applications [28].

The formula employed to calculate the membership values is as follows:

$$f(x) = \begin{cases} 0 & \text{if } x \leq i \\ \frac{x-i}{j-i} & \text{if } i \leq x \leq j \\ \frac{k-x}{k-j} & \text{if } j \leq x \leq k \\ 0 & \text{if } x \geq k \end{cases} \quad (30)$$

Fuzzy membership function for Energy, node centrality, local distance and Output are shown in Figures 4–7.

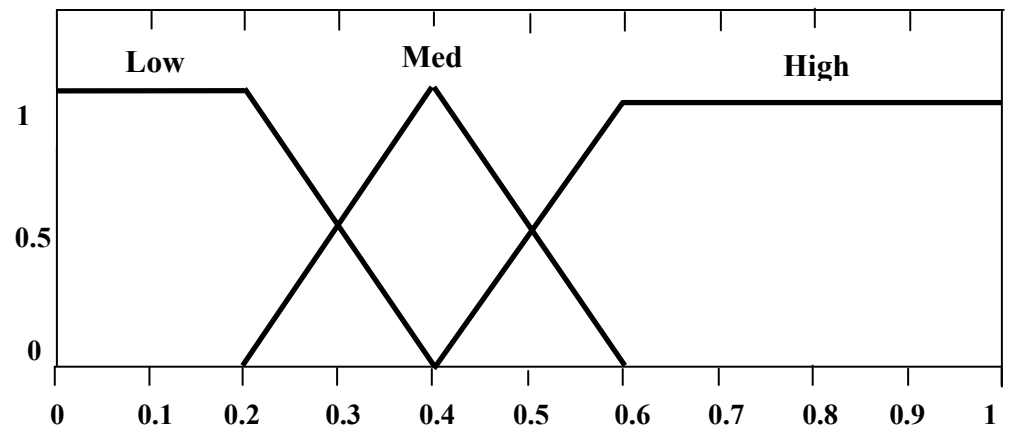


Figure 4. Fuzzy membership function for Energy.

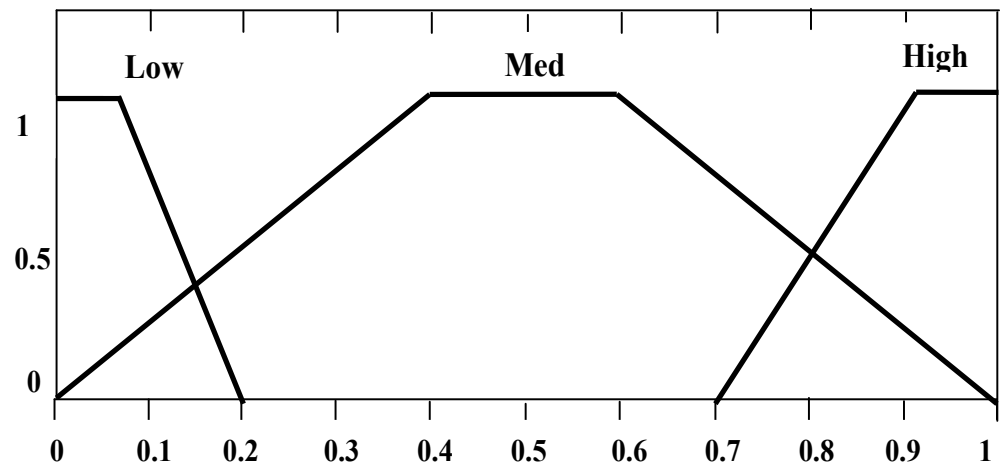


Figure 5. Fuzzy membership function for node centrality.

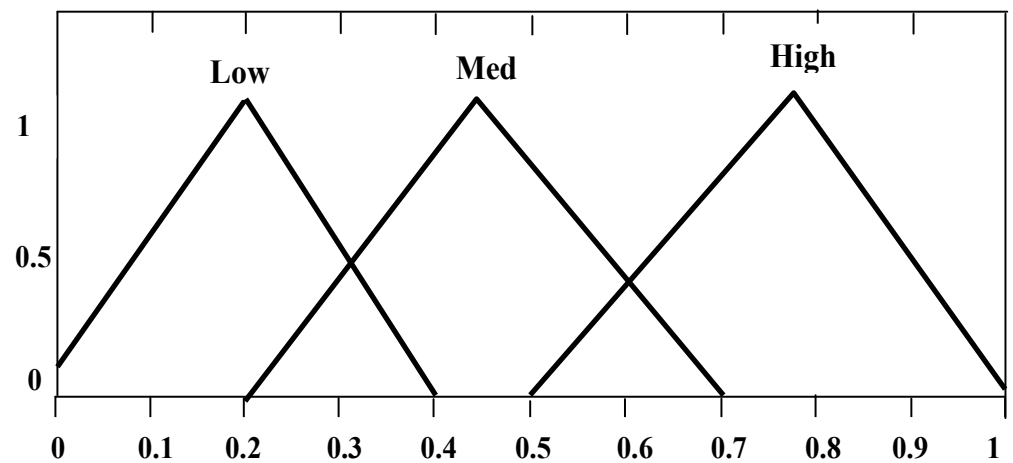


Figure 6. Fuzzy membership function for local distance.

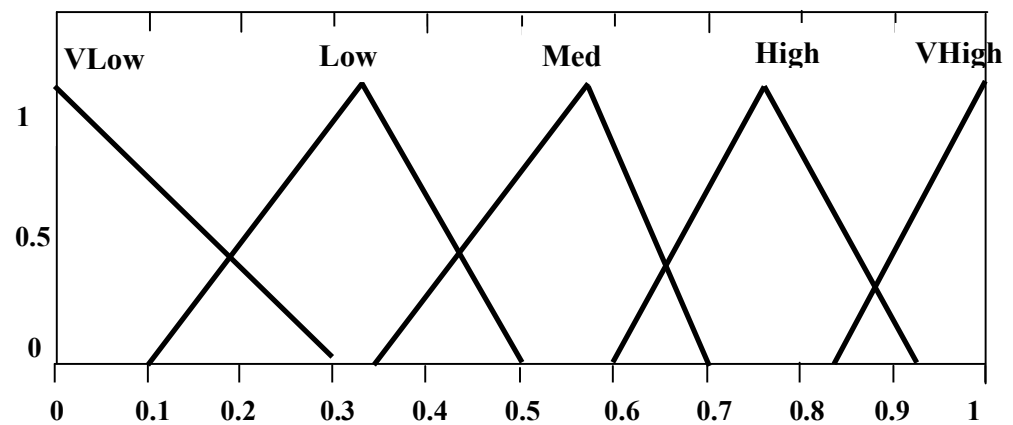


Figure 7. Output function.

Step 4: De-fuzzification:

De-fuzzification is the procedure of making a measurable decision in crisp logic with ambiguous packages and associated with membership degrees. It is the development of mapping an obscure package to a crisp package [29]. The output of the FLS for each sensor node is used for the optimal cluster head generation process.

3.4. Routing

After successfully selecting CHs and SCHs, a proficient routing path to the BS is established between the SN by using HOP Count. “Hello, message” is transmitted by every CH to its neighboring CHs to update its neighbor table with data from different CHs. This hello message encloses SCH HOP-Count data. The next HOP node is selected by the CH on basis of the minimum HOP-count value. The lowest quantity of hops per target hub is considered using Equation (31).

$$HOP_{min, i} = \{min(HOP_j) | j \in N_i\} + 1 \quad (31)$$

where $min(HOP_j)$ = the neighbor CHs j with the fewest hops to the target node.

Updated passages are arranged in climbing requests after the hello bundle gathers at one end of the CHI’s neighbor table (NT). The source CHI’s neighboring table is shown in Table 2. The CH with the fewest HOPs is chosen as the next CH. As shown in Figure 8, the information packet is sent to CH18 by CH4, CH6, CH13, and CH16 [30].

Table 2. CH₁’s Neighbor table.

Neighbor CHs of CH ₁	Hop Count
CH ₄	4
CH ₂	5
CH ₃	5

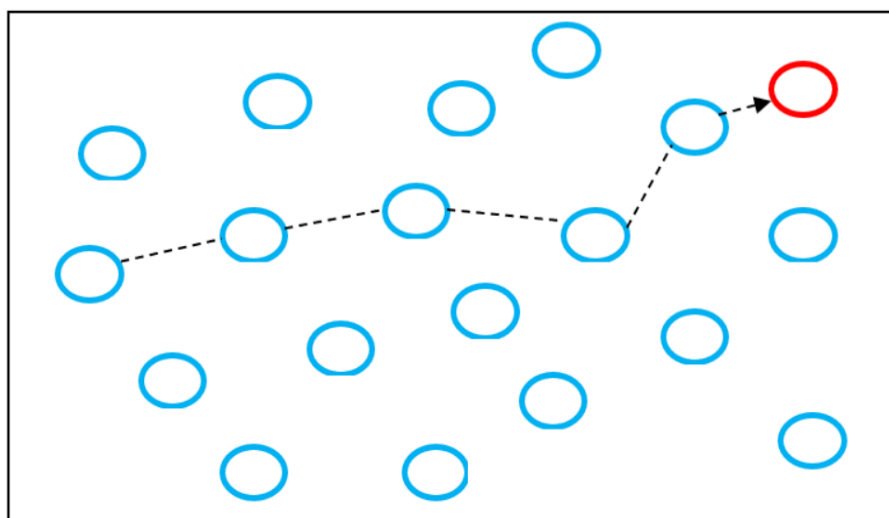


Figure 8. Hop-count-based efficient routing.

4. Result and Discussion

The investigational results of the planned cluster-forming technique in the WSN to improve the QoS and energy parameters are analyzed here. The proposed system was simulated using the NS2 simulator. A 1000×1000 m region with 100 nodes with a transfer limit of 250 m for the simulation was considered. The proposed method was simulated within 50 s. Here, the nodes were clustered and the cluster head was selected by the planned method. This section discusses the effectiveness of the planned strategy for several metrics such as packet delay, delivery rate, energy consumption, efficiency, and network longevity. The simulated measurement of our planned strategy is shown in Table 3. In this simulation, the IEEE 802.11 wireless protocol was used.

Table 3. Simulation parameters.

Parameter Name	Value
Number of nodes	100
Wireless protocol	802.11
Area	1000×1000
Simulation time	50 s
Packet size	512
Transmit power	0.660 W
Receiving power	0.395 W
Initial energy	40 J
Transmission range	250 m
Constant bit rate	500 kbps

4.1. Metrics for Evaluation

The system's performance was assessed using typical statistical parameters such as delay, delivery rate, power, efficiency, and NLT. To evaluate system performance, the findings were compared to existing approaches such as PSO, GA and WOA for various standardized value measures.

- Delay:

The average time it takes an information parcel to arrive at a goal. This incorporates all deferrals brought about by the support during the course of disclosure delay, and the interface line remains set up. This measurement is determined by subtracting the time transmitted by the principal parcel source from the time the main information bundle arrived.

- Delay Ratio:

The packet delay rate is the rate used to calculate the amount of data packages transmitted by the source node. Data obtained by the target node are used to compute the rate of loss of information packages during data transfer over the network. It estimates the rate of loss and measures the equal correctness effectiveness of ad hoc routing protocols. A high packet delivery rate is believed to be high on any network.

$$PacketDelayRatio = \sum \text{Numberofpacketreceive} / \sum \text{Numberofpacketsend}$$

- **Throughput:**

Performance can be defined as how many information packages are established by the recipient during an information transfer or as a successful data transfer over time. It includes the average rate of successful packages delivered after the source hub to the target node in any network project. Performance is specified in bits/bytes per second. High performance is the most important factor in any network.

4.2. Performance Comparison

The diagram demonstrates the effects on presentation of equally comparing the planned protocol with the actual protocol. The procedure of cluster formation in planned research work is depicted below shown in Figure 9.

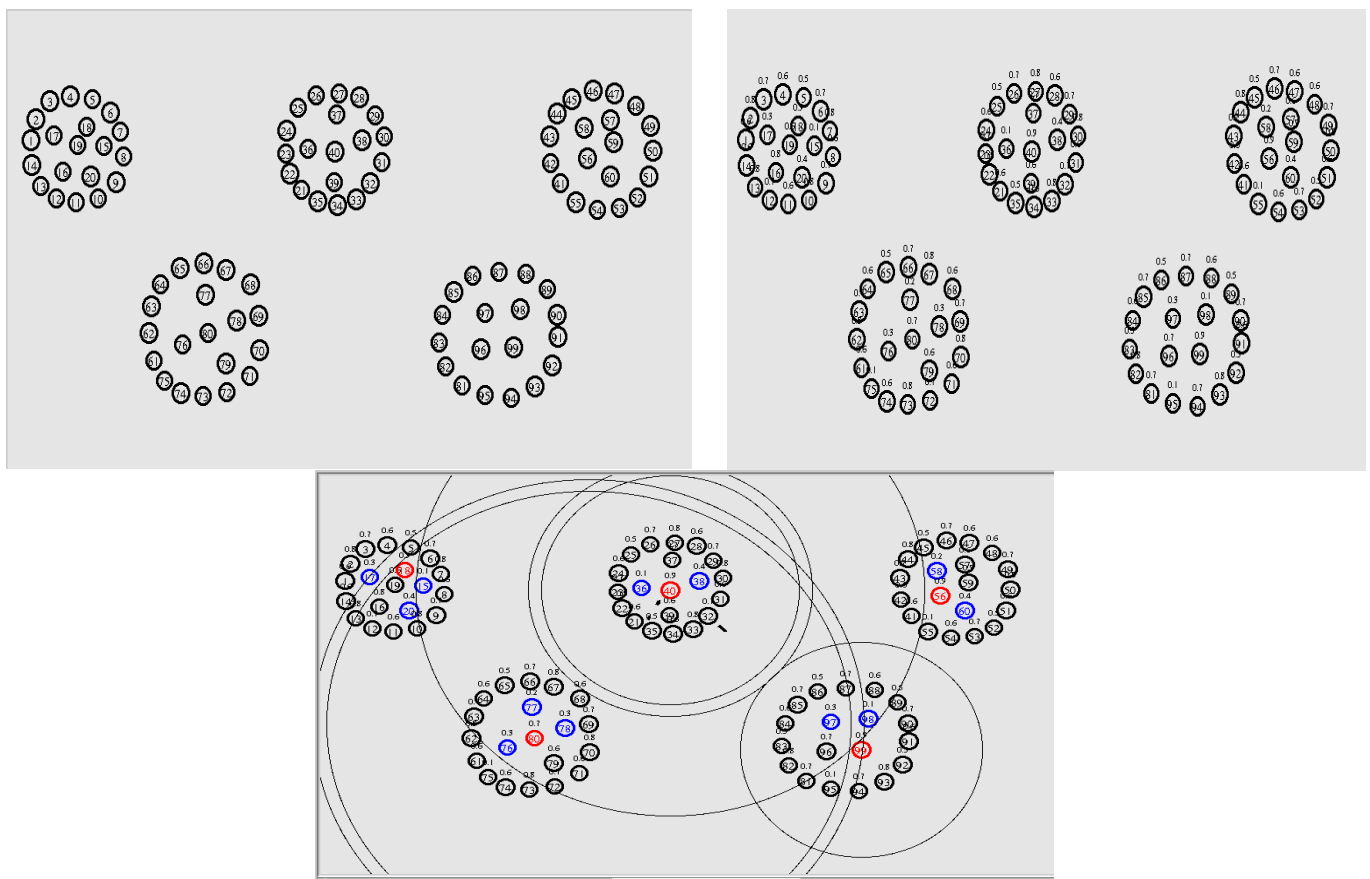


Figure 9. Step by step procedure of cluster formation.

The routing protocol’s package drop rate is indicated in Figure 10, demonstrating the proposed method’s reduced latency when compared to the existing protocols such as PSO, GA and WOA based on network flow.

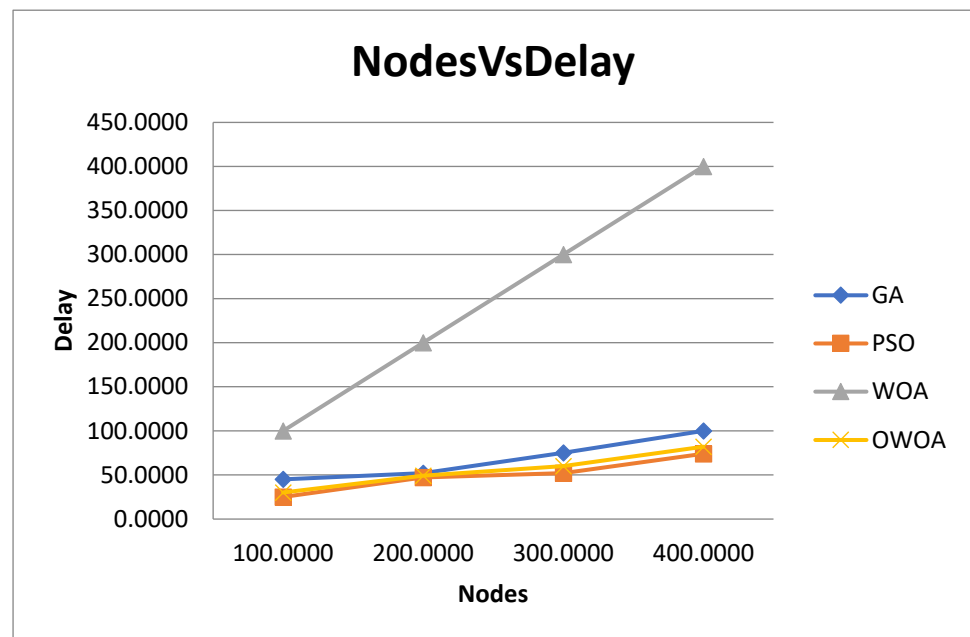


Figure 10. Nodes vs. Delay.

Figure 11 demonstrates the current of nodes in the routing protocol. The graph clearly shows the accuracy of packet delivery compared to the existing ones. Compared to the present techniques such as PSO, GA and WOA, the planned technique provides greater effectiveness in package delivery.

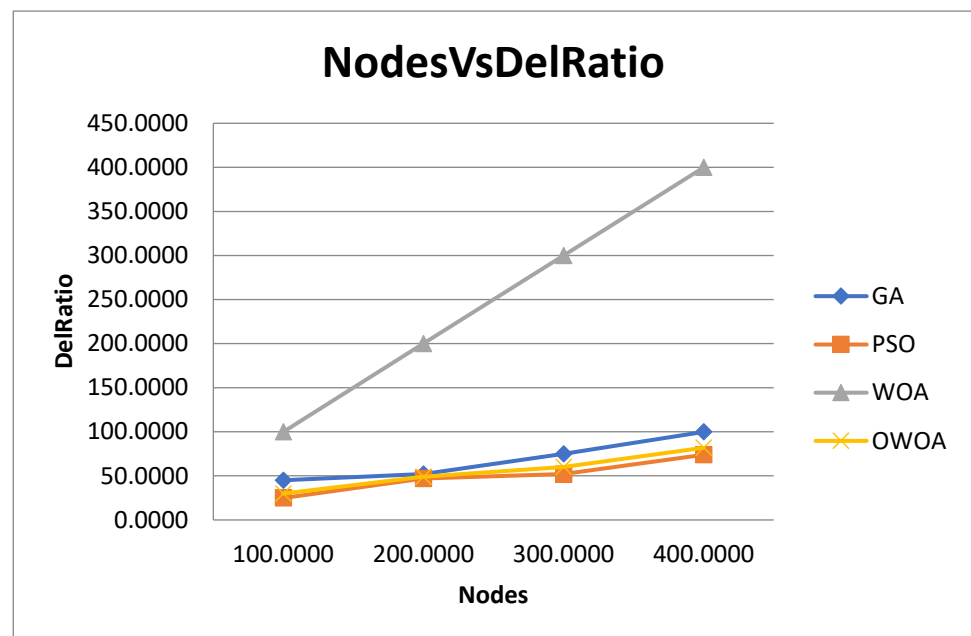


Figure 11. Node vs. Delivery Ratio.

Figures 12 and 13 show the performance metrics of the proposed OWOA algorithm which achieved a more efficient outcome than other existing techniques such as PSO, GA and WOA by varying the nodes.

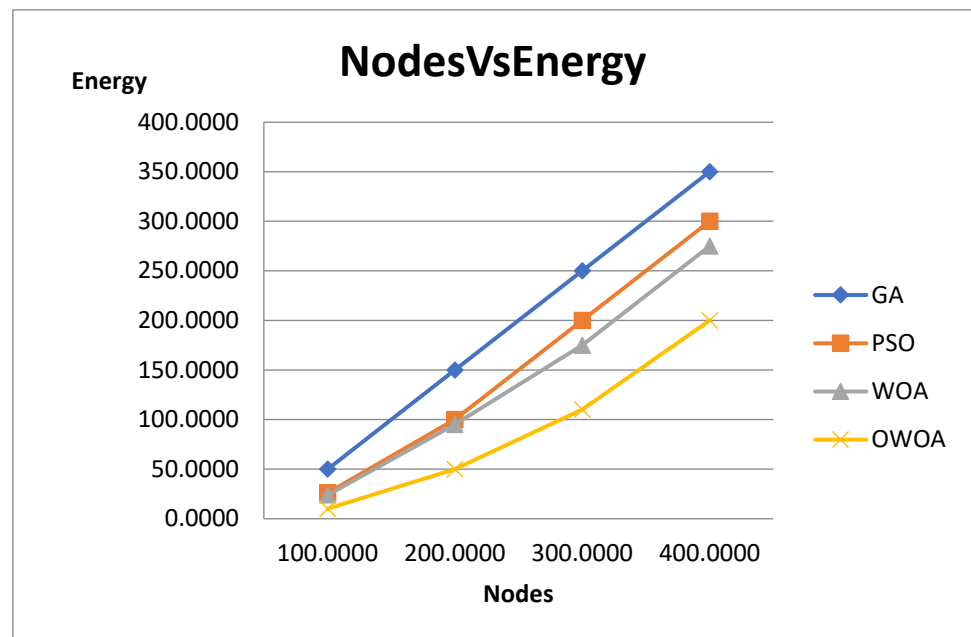


Figure 12. Node vs. Energy.

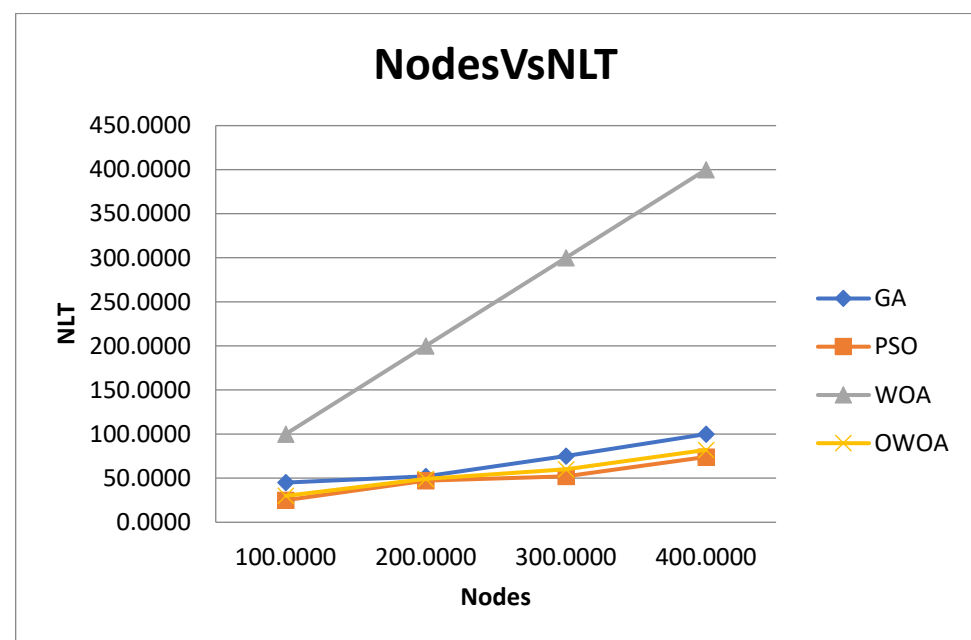


Figure 13. Node vs. NLT.

Figure 14 shows the result of throughput obtained for the proposed OWOA and existing PSO, GA and WOA techniques by varying the nodes. The proposed OWOA algorithm achieved a more efficient outcome than the other algorithms.

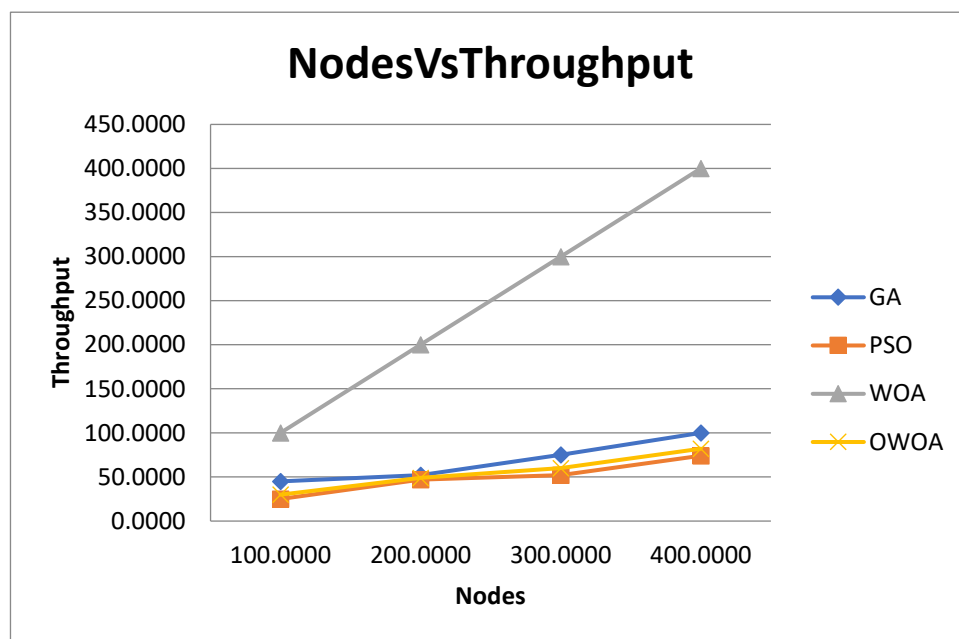


Figure 14. Node vs. Throughput.

5. Conclusions

In this work, AWOA was used to solve the energy consumption problem in WSN. The CH and SCH selection processes were successfully established and tested using AWOA and FIS. The multi-objective function was also designed for the CH selection process. Hop-count-based routing was developed. An Oppositional-based Whale optimization algorithm (OWOA) was developed for multi-constrained QoS routing with the help of AWOA. The performance of the proposed OWOA methodology was analyzed according to the following metrics: delay, delivery ratio, energy, NLT, and throughput. The OWOA was compared with conventional techniques such as PSO, GA, and WOA to demonstrate the efficacy of the proposed methodology. Compared to the existing methods, the proposed method attained an efficient outcome. WSNs are autonomous in nature and are distributed randomly in space. There is no central authority and the deployment of nodes is random, making the process prone to various security threats such as a malicious attack where a compromised node misleads other nodes by imitation. In future, security-aware data transfer using the updated version of AWOA could be implemented.

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