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Optimal Cluster Head Selection in Wireless Sensor Network via Multi-constraint Basis using Hybrid Optimization Algorithm: NMJSOA

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ABSTRACT- Due to its general use in various practical applications, number of innovations in Wireless Sensor Networks (WSN) is receiving a lot of consideration from researchers. It shows significant technological development with excessive capacity since it gives useful information to users in a particular field through real-time monitoring. Due to its characteristics, such as infrastructure-less adoption and resource limitations, wireless sensor networks bring several problems that could impair the system's operation. Cluster based routing in WSN is the major concern in this field that could conflicts with the effectiveness of energy, suitable Cluster Head (CH) selection, protected data transport as well as network lifetime augmentation, demand major consideration, etc. However, it remains challenging to make optimal clustering process of WSN that makes the routing process more effective. Thereby, this work proposes a new Namib Merged Jelly Search Optimization Algorithm (NMJSOA) approach for the optimal CH selection in WSN by the different constraints. Initially, the sensor nodes are grouped together to form the clusters by the k-means clustering techniques. Subsequently, allocating the CH for each cluster by computing the weight function for each cluster depends on the conditions such as energy, delay, distance and security. According to the NMJSOA method, the Namib Beetle Optimization (NBO) searching position and the Jellyfish swam old position are added together to get the best optimum position. Finally, the performance of the suggested model is investigated over the conventional methods in terms of different performance measures.

Keywords: Namib Beetle Optimization, Improved Jellyfish Optimization, K-means Clustering, Cluster Head.

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1. INTRODUCTION

Wireless sensor networks are formed up of tiny devices that interact with one another to gather data [1, 2]. These tiny sensors, known as nodes, include a CPU for processing data, memory for storing data, an internal battery for power, and a transmission device for receiving and transmitting messages. Every sensor node's size change depending on its purpose. A wide range of uses, including ecological or habitat surveillance, intelligent battlefields, automated homes, traffic control, etc., are being predicted and expanded for WSN. Routing in WSN [3-5] provides several outstanding benefits, including adaptable communication and layout, minimal energy consumption during data transmission [6, 7]. Moreover, the process of cluster-based routing is the important factor in WSN. The process of grouping the population or information points so that they are more similar to one another than the ones in other categories is known as clustering [8, 9]. The lifespan and flexibility of a sensor network can be increased by clustering. As a result of lowered inter-cluster interaction and clustering in WSN [10, 11] also reduces the routing database size, power consumption, and transmission delay. Single CH and multiple Cluster Members (CM) are the two different types of components that make up a cluster [12, 13]. The CH is specifically in charge of gathering information packets from its CMs [14, 15].

Regarding approaches to establish protocols for the method of clustering in WSN, numerous studies have been conducted [16, 17]. The subsequent list includes many of the clustering techniques that have been suggested in the literature namely, Fast Local Clustering Service (FLOC), Low Energy Adaptive Clustering Hierarchy (LEACH) [18], Power Efficient Gathering in Sensor Information System (PEGASIS), Hybrid Energy Efficient Distributed Clustering (HEED), and Energy Efficient Unequal Clustering (EEUC). LEACH [19, 20] represents one of the greatest interesting cluster-based routing techniques in this area. The main drawback in such protocols is that it does not offer dynamic multilayer clustering; likewise, the type of clustering in such protocols can't be modified without a new design. As a result, these protocols are ineffective

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in the challenging circumstances of connected sensors. The current clustering technique [21-23] has a number of problems, including a short network lifetime, a high use of energy, an absence of modification to different networks, inadequate stability, nodes death, a delay in data transfer, difficulty managing large-scale WSNs, inadequate evaluation of remaining energy nodes, extra costs and energy protection, and an imbalanced lifelong of nodes. The following are this paper's main contributions:

- To create a multi-objective weighted function that decides on a cluster's most effective CH node and decrease an inequality in the network's energy usage, distance, delay and security.
- Proposed a multi constraint basis NMJSOA for the optimum CH selection in WSN.

The remaining work of this paper is structured as follows. Literature survey is mentioned in *section 2*. *Section 3* illustrates the suggested work for the optimum CH selection. *Section 4* represents the results and analysis of the recommended work. *Section 5* presented the conclusion of the entire work.

2. RELATED WORK

The characteristics and difficulties of the conventional cluster head selection models in WSN are discussed in the literature review. Even if the CH selection process is a useful technique for clustering, there are still a lot of problems with the traditional approaches. In order to address these problems, a successful clustering approach needs to be developed. This section is an explanation of some traditional algorithms and their drawbacks. Particle Swarm Optimization (PSO) [24] offers a better way to extend the lifetime of the entire network and has a lower node mortality rate. Network lifetime is improved and balanced consumption of energy is achieved with LEACH-based selection of CH [25]. The main issues with this technique are that it gives no information regarding the CHs in a network and that the way the clusters are distributed is randomly. LEACH-MAC [26-28] has extended network lifetime typically and further controls CH selection's intrinsic unpredictability. However, they have certain drawbacks, such as trying to implement the suggested model in an unpredictable network and in a setting that is constantly changing. Longer network lifetime is achieved through Hausdorff clustering [29], which is also relevant for initial energy distributions that are not uniform. Inadequate cluster identifiers and uncertain terminating requirements are regarded as this methodology's two greatest challenges. Improved throughput and information recovery are provided by Cluster Head Selection by Randomness with Data Recovery (CHSRDR) [30]. Even still, there is an opportunity for enhancements to the way tasks are distributed as well as terms of effectiveness. The nodes are closer together according to Firefly with Cyclic Randomization (FCR) [31], and there are more nodes that are still active. Additionally, the disadvantages are listed as Getting stuck in the local optima and having no memory. PSO [32] performs better in terms of a lifetime, average quantity of packets, etc. and has a superior total energy usage. However, efforts are still being made to employ in multimodal sensor networks despite the lack of device movement in higher dimensional regions. The average residual energy and Stabilization period are both greatly increased by Fuzzy Based Balanced Cost CH Selection Algorithm (FBECS) [33]. This strategy's main flaws are that it gives each factor the same weight and is weak by nature. The Hyper Exponential Reliability Factor Based Cluster Head Election (HRFCHE) [34] system achieves the shortest average delay and uses less energy overall. Cluster Chain Weight Metric (CCWM) [35] has improved balance of loads, decreased communication expenses, and decreased energy usage [36]. However, there is a lot of network overhead, and the load is split equally. With Fractional Lion (FLION) [37], the node lifespan increases and the delay is minimal. However, there is an absence of multimodal and unimodal techniques, and improved convergence is required. Energy Efficient Cluster Head Selection using an Improved Version of the Grey Wolf Optimization (EECHIGWO) [38] deals with enhanced network stability and increased lifetime of the network. PSO [39] achieves improvement in network's lifetime and enhanced size of the network.

3. PROPOSED WORK FOR OPTIMAL CH SELECTION

The most crucial technique for extending network lifetime in WSNs is clustering. Sensor nodes are grouped to form clusters and CHs are chosen for every cluster. Data from each cluster's nodes is collected by CHs, which then send the gathered data to the base station. Making the right CH choices in WSNs is a significant problem. In our suggested model, a new cluster head selection framework is selected with four criteria namely, energy, delay, distance and security. In this paper, multi constraints are considered for the cluster head selection method. The proposed model in brief as below:

- At first, the sensor nodes are group together under the clustering process. In our proposed work, the clustering process is done by k-means clustering algorithm.
- After the clustering formation, the optimum cluster head is selected by a new NMJSOA algorithm that combines the Namib Beetle Optimization and Jelly Fish Optimization (JFO).
- The new optimal CH selection is carried out under four constraints like energy, delay, distance and security.

3.1 Step.1-Clustering via K-means Clustering

Clustering in sensor nodes has been widely pursued by the research community in order to solve the scalability, energy and lifetime issues of sensor networks. Clustering algorithms limit the communication in a local domain and transmit only necessary information [40, 41]. A group of nodes form a cluster and cluster members generally communicate with the cluster head and the collected data are aggregated and fused by the cluster head to conserve energy. Accordingly, this paper considers the k-means [42] clustering procedure as the node grouping method. Here, the nodes are clustered into K clusters using iteration in the non-hierarchical clustering technique known as K-means. *Figure 1* shows the clustering process. The K-means method's processes can be described into the form as follows:

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- Choose the starting centroid node (cluster center) of each group and indicate the cluster member.
- For allocating cluster members to the closest centroid node, compute the Euclidean distance among each cluster member as well as the cluster center.
- To establish a new centroid node in each cluster, calculate the distance among each cluster member with the new cluster center.
- Keep repeating steps (ii) and (iii) until the cluster center is stable or identical in each cluster.

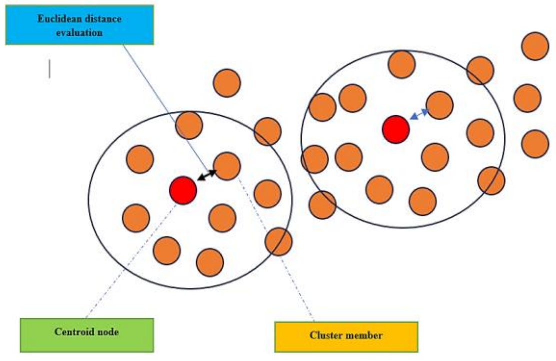

Figure 1: Clustering process

3.2 Step.2-Cluster Head selection using NMJSOA

In this paper, the 2nd step takes place under the cluster head selection through multiple constraints namely, energy, delay, distance and security by using NMJSOA. It is explained briefly as follows. Namib Beetle optimization merged with Jellyfish optimization algorithms are the hybrid optimization algorithms used in this paper. *Figure 2* illustrates the overall cluster head selection process framework.

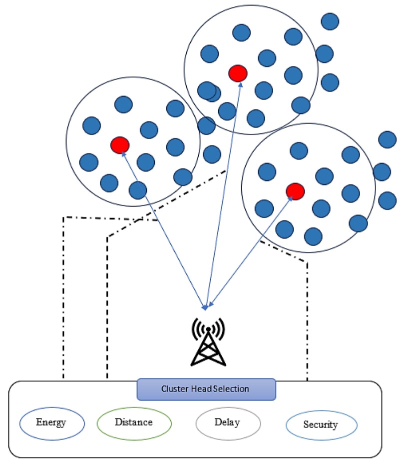

Figure 2: Overall framework for cluster head selection

3.2.1 Energy, E_c

Battery consumption is the main issue in WSN. The sensor nodes reduce their energy due to the data transmission into the base station. Once the battery of the sensor node is depleted, it cannot be rechargeable and also their power supply is completely neglected. This reduction of energy is based on various applications like transmitting or receiving the data, sensing and grouping. So, the total energy needed to transmit the data should be less. In our model, the energy consumption, E_c [43] for Data transmission and receiving among paired sensors l, m is mathematically expressed in *equation 1*.

$$E_c(\beta, e) = \begin{cases} \beta * E_d + \beta * E_{fs} * D^2(l,m), \text{if} D(l,m) \leq D_{max} \\ \beta * E_d + \beta * E_{mp} * D^4(l,m), \quad \text{Otherwise} \end{cases} \quad (1)$$

Where, β= No. of bits of data to be transmitted
E_d= Energy consumed per bit for data transmission
E_{fs}= Energy consumed bit per square meter for free space data transmission
E_{mp}= Energy consumed bit per square meter for multi-path data transmission
D(l,m)= Distance between sensor l and m
D_{max}= Threshold distance calculated as $\sqrt{\frac{E_{fs}}{E_{mp}}}$

3.2.2 Delay, Ds

The delay constraint in WSN is referred to as the period from the distributed data of the time unit to the time unit, with no available nodes to delay the data. Therefore, the delay is more connected to the probabilistic transmission device's delay. *Equation 2* shows the mathematical calculation of delay, which is the ratio between distance to the speed.

$$Delay(D_s) = \frac{Dis\tan ce}{Speed} \quad (2)$$

3.2.3 Distance, δ

Distance (δ) is the separation between objects in similar clusters and those in dissimilar clusters. Two types of distance are calculated is Inter-cluster distance and Intra-cluster distance. The distance among the nodes in the cluster is designed by using Euclidean, Manhattan and Chebychev distance formulas. Let Q and R be the clusters, the distance between two nodes m and n belonging to Q and R, correspondingly. The number of nodes in clusters Q and R are $|Q|$and $|R|$, respectively. Average Linkage Distance and Complete Diameter Distance are the two distances calculated by inter-cluster and intra-cluster distance respectively.

Average Linkage Distance: Considered as the average distance among all of the objects in two separate clusters, the averaged linkage distance is stated in *equation 3*.

$$\delta(Q,R) = \frac{1}{|Q||R|} \sum_{\substack{m \in Q \\ n \in R}} d(m,n) \quad (3)$$

Complete Diameter Distance: Described as the separation among two items in the identical cluster that are the furthest distant from one another, the complete diameter distance is calculated in *equation 4*.

$$\delta(Q) = max\{d(m,n)\} \quad (4)$$

3.2.4 Security, S

The various components of the security system that are described below are the risky mode, the γ -risky mode and the security mode [44].

Risky mode- For supporting an ideal CHS, this method chooses a current CH and assumes all associated risks. Therefore, while selecting CH, this mode is seen as an aggressive mode.

γ -risky mode - The CH that can handle the highest level of γ -risk is chosen depending on the "γ -risky mode." As a result, γ -represents a probability metric with values of 0 and 1 of 100% that respect to the security and risky modes.

Security mode- This selection promotes the CH that satisfies security requirements. The security rank as well as security requirements related to CHS are shown in Eq. (1) by the letters S_R and S_N. The node is regarded as CH if $S_N \leq S_R$.

Equation 5 illustrates the possibility of security limitations. Furthermore, "the risk must be below fifty per cent if the selected CH accomplishes the stated $S_N > S_R$. The selection procedure is going to be carried out if the condition were $0 < S_N - S_R \leq 1$, whereas it would be delayed if the condition were $1 < S_N - S_R \leq 2$. The CHS procedure could not be finished, hence the state $2 < S_N - S_R \leq 5$should continue to perform the associated function".

$$f_{risk} = \begin{cases} 0, if S_N - S_R \leq 0 \\ 1 - e^{\frac{(S_N - S_R)}{2}}, if 0 < S_N - S_R \leq 1 \\ 1 - e^{\frac{3(S_N - S_R)}{2}}, if 1 < S_N - S_R \leq 2 \\ 1, if 2 < S_N - S_R \leq 5 \end{cases} \quad (5)$$

3.3 Objective Function of CH Selection

The objective function [45] for the selection of CH is based on the minimum fitness function of every constraint. In our proposed, two objective functions f1 and f2 are considered under the constraints like energy consumption, distance, delay and security, respectively. The objective function f_1 is computed in *equation 6* and *equation 7*. Where $w_1$represents the weight of the energy consumption constraint, w_2 denotes the weight of the distance constraint and w_3 represents the weight of the delay constraint. Similarly, *equation 8* and *equation 9* show the objective function f_2. Where, $w_4$is the weight of security constraint. Therefore, the two objective functions are combined for the proposed model of CH selection, which is mathematically represented in *equation 10*. Where μ represents the weight parameter in the range of [0,1].

$$obj(f_1) = min(fit_1) \quad (6)$$

$$fit_1 = min(w_1 * E_c + w_2 * \delta + w_3 * D_s) \quad (7)$$

$$obj(f_2) = min(fit_2) \quad (8)$$

$$fit_2 = min(w_4 * (1 - security)) \quad (9)$$

$$F = \mu * fit_1 + (1 - \mu) fit_2, 0 < \mu < 1 \quad (10)$$

3.4 Namib Beetle Merged Jellyfish Search Optimization Algorithm (NMJSOA)

An important step in a WSN design that primarily focuses on minimizing network energy usage is choosing the cluster head. It arranges the sensor nodes into a complex network cluster in order to build one that uses less power and has a long lifespan. To overcome these issues, this paper focused on a selection of optimal CH through multiple constraints like energy, delay, distance and security by using the NMJSOA. Namib beetle merged with Jellyfish search optimization algorithm is the hybrid optimization method. In this algorithm, the behavior of jellyfish based on the active and passive motion in the ocean for finding their food is considered and the movement of Namib beetle towards the wet area is considered. Both jellyfish and Namib Beetle's old position are added to found one position, which is replaced by the old position of the new position of jellyfish movement in the ocean. This hybrid algorithm is most suitable for obtaining the optimal CH selection under the constraints in terms of energy consumption, distance, delay and security. The Jellyfish Search Optimization (JSO) technique was developed in part as a result of jellyfish activity [46]. The following actions are included in jellyfish's food-finding process:

- The motion of the jellyfish itself inside the swarm.
- Following the ocean current to create a bloom of jellyfish. The following idealized principles are taken into account by the JSO algorithm.
- The temporal control method alternates between the two advancing motions of the jellyfish. Such as motion inside the swarm and movements that follow the current of the ocean.
- Areas with a greater availability of food are more attractive to jellyfish.
- The location and its associated goal function regulate the amount of food found.

Implementing the JSO approach first requires a random initialization for spreading solutions throughout the issue's search range. After carefully examining each response, the site with the highest fitness ratings is chosen as the supply of food. From that moment on, depending on the time control factor, each jellyfish's movement is refreshed either in the direction of the ocean flow or towards development within the swarm.

3.4.1. Step.1-Jellyfish in ocean current

Ocean currents contain a lot of nutrients, jellyfish are drawn to them. By combining the motion vectors from every jellyfish in the ocean to the jellyfish holding the current optimum location, it is possible to regulate the direction of the ocean current (i.e., $\overrightarrow{drift}$). The mathematical calculation of ocean current direction is expressed in *equation 11* [47].

$$\begin{aligned} \overrightarrow{drift} &= \frac{1}{n} \sum \overrightarrow{drift_k} \\ &= \frac{1}{n} \sum (x^c - a^c x_k) \\ &= x^c - a^c \frac{\sum x_k}{n} \\ &= x^c - a^c m \end{aligned} \quad (11)$$

Where, n is the overall count of jellyfish, while x^cdenotes the current best position of jellyfish current-best position within the population. m denotes the average location of the jellyfish swarm, while a^c denotes the attraction factor. Let DF be the difference between the jellyfish's preferred position right now and the swarm's average location, which is expressed in *equation 12*.

$$DF = a^c \times m \quad (12)$$

Assume that jellyfish would have a regular spatial distribution across each dimension, giving the probability for every jellyfish location and it is calculated in *equation 13* According to this distribution, every jellyfish location is close to$\pm\beta\sigma$. Here, β stands for the distribution coefficient, which is assumed to be '3' and σ stands for the standard deviation for the distribution under consideration, which may be calculated using *equation 14* near the swarm's mean location. Therefore, the drift can be mathematically denoted in *equation 15*. Therefore, the updated position of every jellyfish is evaluated in *equation 16*. Here, $x_k(t)$ represents the k^{th}jelly position at time t, which corresponds to the iterations in the particular algorithm.

$$\mathrm{DF} = \beta \times r^{\alpha}(0,1) \times \sigma \quad (13)$$

$$\sigma = r^{\gamma}(0,1) \times m \quad (14)$$

$$\overrightarrow{\mathrm{drift}} = x^c - \beta \times r(0,1) \times m \quad (15)$$

$$x_t(t+1) = x_k(t) + r(0,1) \times \overrightarrow{\mathrm{drift}} \quad (16)$$

3.4.2. Step.2-Jellyfish swarm: The proposed position update process

Swarm is the name for a huge group of jellyfish in the ocean. Jellyfish movement in a swarm is divided into active (type B) and passive (type A) movements. Jellyfish move in a type A, or passive, manner as the swarm forms. *Equation 17*, which describes how the jellyfish travel around their own location and then update every other's positions. The jellyfish eventually simulate type B movement. Where, γ denotes the coefficient of movement that is related to the motion length around the position of Jellyfish. The value of γ is taken as (0,1), according to the mathematical calculations. ub and lb indicates the lower and upper bound in the search area, respectively. Rearrange the *equation 17* to calculate the previous position of jelly, which is in *equation 18*.

$$x_k(t+1) = x_k(t) + \gamma \times r(0,1) \times (ub - lb) \quad (17)$$

$$x_k(t) = x_k(t+1) - \gamma \times r(0,1) \times (ub - lb) \quad (18)$$

In the same time, Namib beetle optimization [48] is immersed in the Jellyfish search optimization. The Namib beetles move to the highest elevations to gather water. They are searching these hills for spots with higher moisture and elevation so they can reach more water. When they reach the highest points of the dunes, they lift their bodies to expose themselves to the air currents carrying moisture, which they then take in and guide into their mouths. In our proposed work, the movement of the Namib beetle towards the web areas is considered. The Namib beetles feel larger amounts of moisture in the last iteration because they are closer to the ideal solution or they can absorb more moisture with a higher coefficient in the region where the ideal beetles are most effective at absorbing moisture. It can be calculated as per *equation 19*, where, $NB_j^{new}$and NB_j^{old}represents the new and old position of a beetle that desires to move, respectively. NB_i indicates the location of a beetle that attracts other beetles. *Equation 20* is used to determine the levy, a random vector that represents the movement of beetles. U and V are two independent random vectors that fluctuate between 0 and 1, while β is a constant value of 1.5.

$$NB_j^{new} = NB_j^{old} + Hum.\left(NB_i - NB_j^{old}\right) + levy \quad (19)$$

$$\mathrm{levy} = \frac{u}{|v|^{\frac{1}{\beta}}} \cdot \left|\frac{\Gamma(1+\beta).\sin\left(\frac{\pi}{2}\beta\right)}{\Gamma\left(\frac{1+\beta}{2}\right).\beta.2^{\frac{\beta-1}{2}}}\right|^{\frac{1}{\beta}} \quad (20)$$

The $NB_j^{old}$is calculated by rearranging *equation 19*, which can be expressed mathematically in *equation 21* and *equation 22*.

$$\mathrm{NB_j^{new}} = \mathrm{NB_j^{old}} + \mathrm{NB_i.Hum} - \mathrm{NB_j^{old}.Hum} + \mathrm{levy} \quad (21)$$

$$\mathrm{NB_j^{old}} = \mathrm{NB_j^{new}} - \mathrm{NB_i.Hum} + \mathrm{NB_j^{old}.Hum} - \mathrm{levy} \quad (22)$$

Proposed position update: From both JSO and Namib Beetle Optimization (NBO), *equation 18* and *equation 21* are added to get the final position *equation 23* which is the updated old position, which is substituted in the *equation 18* of the JSO. The final proposed position update is expressed in *equation 23*, where, the random value is replaced by MS and Dyadic Transformation map [49] based on the chaotic function. *Equation 24* represents the MSDT map function, here, $\lambda \in (0.35,5)$ and $r \in (1,4)$.

$$x_k(t) = \frac{2x_k(t+1) - \mathrm{NB_i.Hum} - \gamma \times r(0,1) \times (ub - lb) + \mathrm{NB_j^{old}.Hum} - \mathrm{levy}}{2} \quad (23)$$

$$x_{n+1} = \begin{cases} \frac{r\lambda 2x_n}{\lambda(1-2x_n)^2+1} (\mathrm{mod}\ 1), 0 \le x_n < 0.5 \\ \frac{r\lambda(2x_n-1)}{\lambda(2-2x_n)^2+1} (\mathrm{mod}\ 1), 0.5 \le x_n < 1 \end{cases} \quad (24)$$

A jellyfish (m) in addition to the present jellyfish of interest is picked at random in type B movement. After that, a vector is created from the jellyfish of interest (k) to the jellyfish chosen at random (m) which determines the jellyfish's path. The quantity of food available at the jellyfish's (m) position determines the movement's direction. When there is more food at the jellyfish position (m) than there is at the jellyfish position (k), the latter goes in the direction of the former, however, when there is less food at the m^{th} jellyfish location, the k^{th} jellyfish travels farther from the earlier jellyfish. Consequently, each jellyfish moves in this manner to find the optimal feeding spot in the swarm. *Equation 25* and *equation 26* show the path of a jellyfish's motion and its most recent position, respectively. Where, $FF$is the fitness function, $\overrightarrow{step}$ is calculated in *equation 27* and *equation 28*.

$$\overrightarrow{\mathrm{direction}} = \begin{cases} x_m(t) - x_k(t); \mathrm{FF}(x_k(t)) \ge \mathrm{FF}(x_m(t)) \\ x_k(t) - x_m(t); \mathrm{FF}(x_k(t)) < \mathrm{FF}(x_m(t)) \end{cases} \quad (25)$$

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$$x_k(t+1) = \overrightarrow{step} + x_k(t) \tag{26}$$

$$\overrightarrow{step} = r(0,1) \times \overrightarrow{direction} \tag{27}$$

$$\overrightarrow{step} = x_k(t+1) - x_k(t) \tag{28}$$

3.4.3. Time control component

The type of movement that jellyfish execute is controlled by a temporal control system. Both actions are controlled by the time element. i.e., the way jellyfish move both toward the ocean flow as well as inside the swarm (i.e., type A and type B motion). The process of selection is controlled by the time control system, which uses a threshold constant, $k_0$and a time control function $C_F(t)$ that ranges arbitrarily from 0 to 1. *Equation 29* mathematically expresses the time control element. Where, i_{max}denotes the maximum number of iterations.

$$C_F(t) = \left| \left(1 - \frac{t}{i_{\max}}\right) \times ((2 \times r(0,1)) - 1) \right| \tag{29}$$

In this case, k_0 is assumed to be 0.5, which is the average of zero and one. The jellyfish moves forward within the jellyfish bloom unless the $C_F$value exceeds the k_0 value, in which case they follow the ocean's current. Similar to this, type A and type B movement of the jellyfish within the swarm is imitated using a time-controlled pseudo-code $(1 - C_F(t))$. A jellyfish exhibits type A movement when the $(1 - C_F(t))$ value is smaller than $r(0,1)$ and type B movement otherwise. The probability $(1 - C_F < r(0,1))$is greater than that of $(1 - C_F > r(0,1))$ because the value $(1 - C_F(t))$increases over time from zero to one. Because of this, type A motion is initially preferred over type B motion. Movement of type B, as opposed to type A, is more frequent throughout time. *Figure 3* shows the flowchart of the NMJSOA technique.

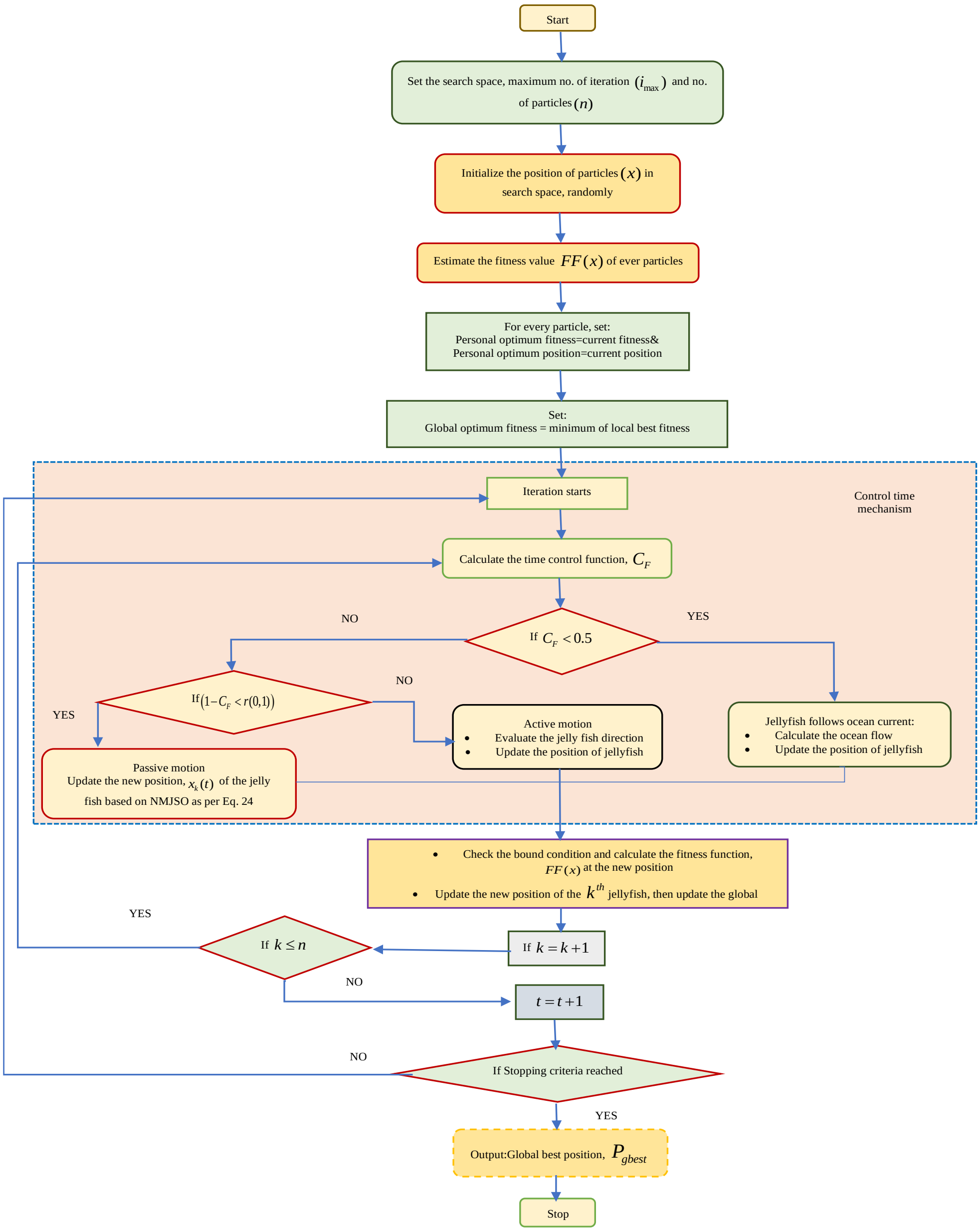

Figure 3: Flowchart of NMJSOA approach

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4. RESULTS AND DISCUSSION

4.1 Simulation Procedure

The proposed cluster head selection model was simulated employing MATLAB. Further, the MATLAB version was "MATLAB R2018a" as well as the processor utilized was "Intel (IR) Core(TM) i5-1035G1 CPU @1.00GHz 1.19 GHZ" and the installed RAM size was "20.0 GB (19.7 GB usable)".

4.2 Performance Analysis

Furthermore, the effectiveness of both the NMJSOA and traditional approaches was assessed in terms of Residual energy, delay, risk, alive nodes, the total number of packets transmitted to the BS, and distance. Moreover, the NMJSOA method was compared against state-of-the-art approaches like EECHIGWO [38] and OCHSPSO [39]. Additionally, it was contrasted with traditional algorithms including PSO, Spider Monkey Optimization (SMO), Grasshopper Optimization Algorithm (GOA), JSO, and NBO. Also, the energy model is shown in *figure 4*. The node distribution of the energy model is organized as X-dimension (in meters) = 100, Y-dimension (in meters) = 100.

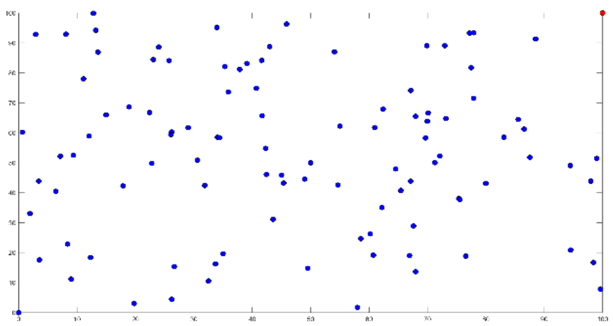

Figure 4: Energy model

4.3 Analysis on Delay and Distance

The delay and distance analysis on NMJSOA over Optimal Cluster Head Selection using PSO (OCHSPSO) [39], Energy Efficient Cluster Head Selection using an Improved Version of the Grey Wolf Optimization (EECHIGWO) [38], PSO [32], SMO [50], GOA [51], JSO [46] and NBO [48] for cluster head selection is explained in *figure 5* and *figure 6*. To achieve the best choice of a cluster head, the model needs to achieve minimized ratings for both delay and distance. Likewise, the NMJSOA approach achieved lower delay and distance ratings in comparison to conventional methods. Mainly, the delay rate of the NMJSOA scheme is 0.762×104s in the round 2000, this is much lower than OCHSPSO [39], EECHIGWO [38], PSO [32], SMO [50], GOA [51], JSO [46] and NBO [48]. Similarly, for other rounds, the NMJSOA offered lesser delay ratings. Additionally, round=1500, the least distance rate attained using the NMJSOA scheme is 0.013m, meanwhile the OCHSPSO [39] is 0.058m, EECHIGWO [38] is 0.026m, PSO is 0.062m, SMO is 0.063m, GOA is 0.061m, JSO is 0.035m and NBO is 0.018m, correspondingly. Consequently, the NMJSOA method utilizes a hybrid optimization approach to attain optimal cluster head selection, consistently providing dependable performance through the reduction of delay and distance values.

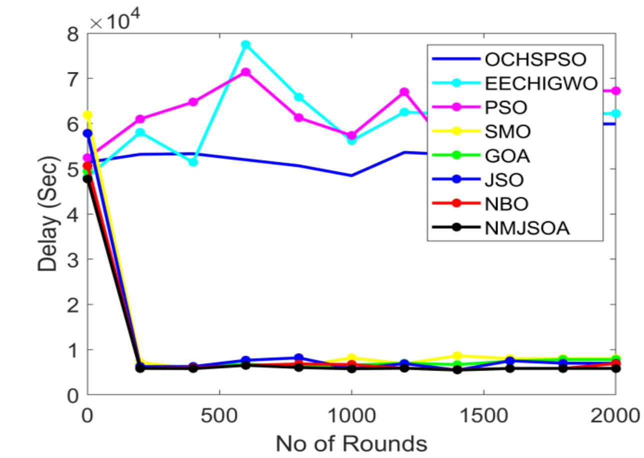

Figure 5: Examination of delay on NMJSOA and conventional methods

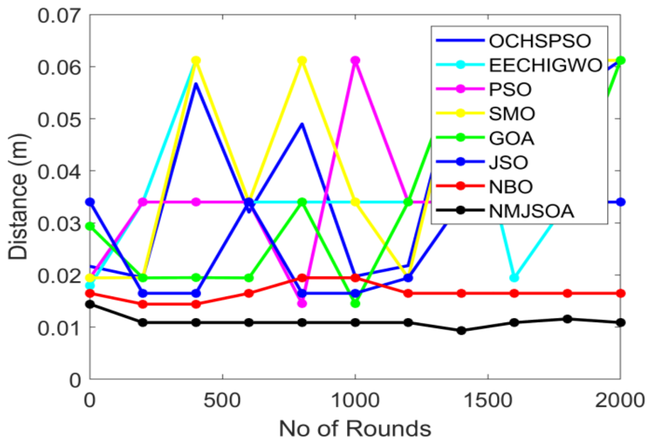

Figure 6: Examination of distance on NMJSOA and conventional methods

4.4 Analysis on Residual Energy and Risk

The validation on NMJSOA is contrasted with OCHSPSO [39], EECHIGWO [38], PSO [32], SMO [50], GOA [51], JSO [46] and NBO [48] about residual energy and risk for cluster head selection is exposed in *figure 7* and *figure 8*. Additionally, for the optimal selection of a cluster head, the residual energy must be higher. Specifically, the highest residual energy achieved with the NMJSOA scheme is 0.159J in the 2000th round, surpassing that of OCHSPSO [39], EECHIGWO [38], PSO [32], SMO [50], GOA [51], JSO [46], and NBO [48].

Figure 8 represents the risk analysis on NMJSOA and conventional schemes for the selection of optimal cluster head. The risk rate of the NMJSOA scheme is 0.215 (round=1000), even though the traditional approaches attained minimal risk rate, notably, OCHSPSO [39]=0.338, EECHIGWO [38]=0.324, PSO=0.316, SMO=0.294, SMO=0.315, GOA=0.298 and NBO=0.254, correspondingly. Therefore, it can be asserted with confidence that when the NMJSOA scheme is employed for selecting the most suitable cluster head, it excels in delivering remarkably efficient solutions while simultaneously preserving a high level of energy efficiency and reducing the risk rate.

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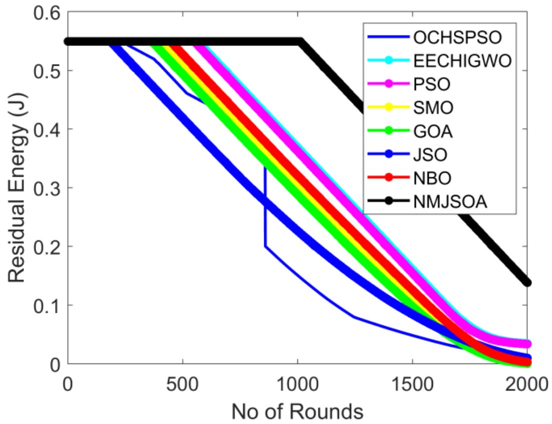

Figure 7: Examination of residual energy on NMJSOA and conventional methods

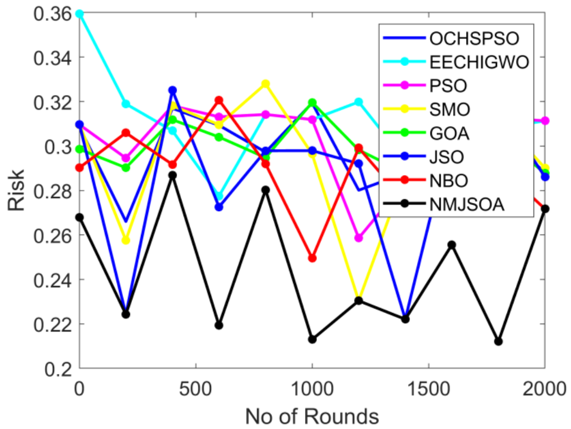

Figure 8: Examination of risk on NMJSOA and conventional methods

4.5 Analysis on Alive Nodes

The alive node assessment on NMJSOA is contrasted with the traditional methodologies for cluster head selection as shown in *figure 9*. Here, the NMJSOA is compared over OCHSPSO [39], EECHIGWO [38], PSO [32], SMO [50], GOA [51], JSO [46] and NBO [48]. Initially, both the NMJSOA and conventional schemes had a higher number of alive nodes. However, as the number of rounds increased, the number of alive nodes gradually improved. Nevertheless, our NMJSOA scheme consistently had the highest number of alive nodes, even in the final round., the NMJSOA gained 35 alive nodes in round 2000, which is extremely higher than OCHSPSO [39], EECHIGWO [38], PSO [32], SMO [50], GOA [51], JSO [46] and NBO [48].

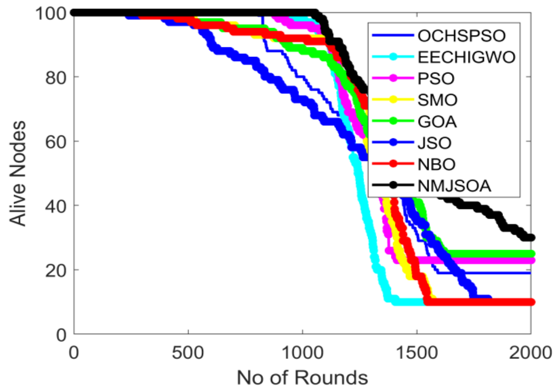

Figure 9: Examinatio of alive nodes on NMJSOA and conventional methods

4.6 Statistical Assessment on Alive Nodes and Remaining Energy

Table 1 and *Table 2* explain the statistical evaluation on NMJSOA is contradicted by NBO [48], JSO [46], GOA [51], SMO [50], PSO [32], EECHIGWO [38] and OCHSPSO [39] for cluster head selection. In this particular context, the reliability of metaheuristic techniques is placed under thorough scrutiny. Consequently, every method undergoes a rigorous evaluation procedure to guarantee the attainment of extremely accurate estimations. To accomplish this goal, a comprehensive assessment is carried out, which encompasses the analysis of vital statistical parameters like minimum, median, standard deviation, mean, and maximum values. Together, these metrics provide a comprehensive insight into the effectiveness and trustworthiness of the strategies being investigated. For the median statistical metric, the NMJSOA acquired the alive nodes of 100, although the NBO (92), JSO (73), GOA (88), SMO (92), PSO (96), EECHIGWO [38] (98) and OCHSPSO [39] (80) scored minimal alive nodes. In addition, the NMJSOA obtained minimal remaining energy of 0.138 under the minimum statistical metric, whilst the NBO [48], JSO [46], GOA [51], SMO [50], PSO [32], EECHIGWO [38] and OCHSPSO [39] scored higher remaining energy.

Table 1. Statistical analysis on alive nodes

Statistical Metrics	NMJSOA	NBO [48]	JSO [46]	GOA [51]	SMO [50]	PSO [32]	EECHIGWO [38]	OCHSPSO [39]
Minimum	30	10	10	25	10	23	10	19
Maximum	100	100	100	100	100	100	100	100
Mean	78.78	68.06	64.55	72.06	67.38	71.08	64.96	69.30
Median	100	92	73	88	92	96	98	80
Standard Deviation	26.63	37.23	32.12	30.10	37.86	34.48	41.41	32.78

Table 2. Statistical analysis on remaining energy

Statistical Metrics	NMJSOA	NBO [48]	JSO [46]	GOA [51]	SMO [50]	PSO [32]	EECHIGWO [38]	OCHSPSO [39]
Minimum	0.138	0.003	0.010	0.001	0.006	0.034	0.035	0.004
Maximum	0.550	0.550	0.550	0.550	0.550	0.550	0.550	0.550
Mean	0.448	0.311	0.255	0.290	0.302	0.337	0.340	0.249
Median	0.550	0.321	0.227	0.288	0.307	0.362	0.369	0.151
Standard Deviation	0.133	0.196	0.182	0.198	0.197	0.191	0.190	0.213

5. CONCLUSION

The proposed NMJSOA model was executed in MATLAB R2018a. Firstly, the sensor nodes were grouped in the form of clusters. Here, the clustering process was done based on the k-means clustering process. Then, a new model Namib Merged Jelly Search Optimization Algorithm was proposed for the CH selection in WSN. For the optimal CH selection, the sensor nodes were dependent on the multiple constraints namely, security, energy consumption, delay and distance. Depending on the constraints the optimal cluster head was selected by using the NMJSOA techniques. Moreover, experimental results were carried out and the performance of the suggested model was better as compared to the traditional techniques. The risk rate of the NMJSOA scheme is 0.215 (round=1000), even though the traditional approaches attained minimal risk rate, notably, OCHSPSO [39]=0.338, EECHIGWO [38]=0.324, PSO [32]=0.316, SMO [50]=0.294, JSO [46]=0.315, GOA [51]=0.298 and NBO [48] =0.254, correspondingly. The proposed NMJSOA algorithm does not consider the routing strategies for the optimal cluster head selection. As a future scope, the algorithm can further incorporate the cluster-based routing for the optimal cluster head selection.

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