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ENERGY EFFICIENT BASED OPTIMIZED K-MEANS AND MODIFIED WHALE OPTIMIZATION ALGORITHM FOR CLUSTER HEAD SELECTION IN WSN

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ABSTRACT

Background: More low-cost and power sensor nodes make up a wireless sensor network (WSN). Using self-organization, the sensor nodes build a wireless network in a specific area. In spite of the fact that people can't close the doors, they can still function normally in any special or wicked environment. Due to a variety of complex factors, effective data transmission between nodes is nearly impossible. When it comes to improving the efficiency of data transmission, clustering is a well-known strategy. The clustering model splits sensor nodes into different groupings. All sensor nodes in a cluster get information from a single cluster head node.
Objective: To improve the network lifetime, throughput and reduce energy consumption by using K-means and modified whale optimization algorithm (KM-MWOA).
Methods: Clustering algorithms play an important role in selecting the most energy-efficient and least-delayed cluster head under such conditions. K-means algorithm is used to select cluster head selection (CHS) and then present the modified whale optimization algorithm (MWOA) to convey packets in multi-hop transmission among CHS and the BS and choose an optimal path. During the global search phase, random population seeding is used to increase the standard WOA. Algorithms are able to discover in the early stages of the search, while also utilizing the search space lengthily in the later stages, by changing the parameters A and b. Reduced intra-cluster communication and improved energy efficiency for sensor nodes are both possible with this clustering scheme.
Result: The KM-MWOA strategy has been realised performance metrics such as Network lifetime, Energy Consumption, Network throughput in MATLAB R2018a with NVIDIA Tesla K80 GPU. The results of the KM-MWOA is compared with Radio Access Technologies, Jellyfish Algorithm.
Conclusion: The KM-MWOA is proposed for extending the lifetime of sensor nodes, reducing the energy consumption and improving throughput. Energy Efficient is diagnosed by using the KM-MWOA models. It is concluded that extending the power of the KM-MWOA supersedes all previous methods (Radio Access Technologies, Jellyfish Algorithm).
Keywords:- *K-Means Algorithm, Modified Whale Optimization Algorithm, Wireless Sensor Network, Energy Consumption; Optimal Cluster Head*

1. INTRODUCTION

Sensor nodes (SNs) are the basic building blocks of a WSN. The SNs are located in a certain area and create a WSN. Communication between WSNs has led to a wide range of applications, from battlefield surveillance to industrial monitoring to danger identification and healthcare monitoring. Furthermore, the energy, compute, and bandwidth are just a few of the resources that make it possible to control the entire WSN. WSNs have arranged exact sensing and symbolized the integration of wireless communications with many nodes in this way. A number of benefits of WSN include its ability to support numerous communication protocols, its inexpensive cost of implementation, and its reduced power usage [1, 2, 3].

The WSN is made up of a large number of SNs. Non-rechargeable batteries power these SNs. As a result, node grouping is critical for providing load balancing, fault tolerance, and network connectivity.

When SNs are grouped into clusters based on a variety of characteristics, the approach known as clustering is used to select a single group leader from among the several groups. There are clusters, and the cluster heads (CH) of the clusters are the leaders of the clusters. Within-cluster communication costs, distances between the CH and its members, nodes' positioning relative to the BS, the residual energy of SNs, and so on [4] are all factors that go into cluster construction.

CHS has been solved using a variety of methods. Regular CHS methods and optimum CHS methods are two subcategories of these strategies. Meta-heuristic and heuristic methodologies can still be used to classify the best CHS methods. Compact and straightforward theories, often grounded in actual evidence, are often used in these tactics for solving optimization problems. Various heuristic approaches have been offered in the literature to cope with heterogeneity [5]. Because of the numerical inefficiency of the search process, heuristic approaches are unsuitable for problems of high dimension or large size. Since the 1980s and 1990s, meta-heuristic optimisation methods have been increasingly prominent. Using meta-heuristic methods, large-scale, complex optimization problems can be solved [6]. Metaheuristic algorithms have shown to be extremely versatile and simple to construct as a result of these properties [7].

- A meta-heuristic technique's capacity to be used to a wide range of optimisation issues is referred to as its "flexibility." Metaheuristics can be used to solve a wide range of problems since they often treat them as if they were black boxes.
- Meta-heuristics tend to be quite straightforward to implement. Simple concepts are the driving force behind their creation. There are many scientific events, animal behaviour, and evolutionary notions that can be used as sources of inspiration.
- Meta-heuristics are better at preventing local optima than typical optimisation methods. As a result of meta-heuristic protocols' stochastic behaviour, they are able to avoid becoming stuck in their local best optima and instead probe the entire search space extensively. The bulk of meta-heuristic algorithms use strategies that are not derived from any other algorithm. The metaheuristic, in contrast to gradient-based optimisation techniques, stochastically optimise problems.

Two basic forms of meta-heuristic procedures exist: population-based and single-solution based. These can also be divided into evolutionary, physics-based, and bio-inspired algorithms based on nature's inspiration. No matter how diverse the meta-heuristic protocols, there was one thing in common that made it possible to divide the search process into two stages: [8, 9] Exploration and exploitation an important part of the search process is the exploration step, which entails thoroughly analysing all potential search locations. Exploitation, on the other hand, is described as the ability to conduct local searches in and around the potential locations discovered during the exploration phase. The stochastic nature of meta-heuristic techniques makes it difficult to find a balance between examination and misuse. WSNs were used to perform CHS using the vast majority of the methodologies that researchers devised. However, further advancements are needed to stabilise energy and increase the lifespan of WSNs.

Our primary goal is to extend the life of sensor nodes. The sensor nodes limited power, limited compute capability, limited storage capacity, and short-range communication is some of the most difficult difficulties to overcome in WSNs. To extend the lifespan of a sensor node, clustering is one method that is employed. Clustering relies heavily on the selection of CH and the creation of clusters. The modified WOA algorithm is an effective approach to select the cluster head in the k-means algorithm for cluster formation.

The basic introduction about WSN with problem statement is given in Section 1, where the study of existing techniques with its limitation is given in Section 2. Section 3 depicts the methodology and system model, as well as the model's intended use. Section 4 outlines the numerous measures that can be used to compare the proposed model to existing methodologies. Section 5 represents the conclusion, scientific contribution, and future work.

2. RELATED WORKS

Using particle swarm optimization (PSO), Rao et al. [10] created an energy-efficient CHS (ECHS) protocol named PSO-ECHS. Particles and objective functions are encoded effectively in this protocol. Numerous limitations, in order to optimise the suggested PSO algorithm's energy efficiency. There is a downside to this strategy in that a random group of nodes are chosen to be CHS at first. The PSO-based CHS was developed after this random selection. It was postulated by Daneshvar and colleagues [11] that CHS may be selected using GWO. A node's residual energy and expected energy consumption determine the outcomes for picking

CHS. The proposed technique uses the same clustering method for a number of successive stages in order to increase energy efficiency. In this way, the clustering algorithm is able to conserve the energy needed for the process of reforming it. Improvements are needed to make networks last longer with this strategy, because the initial node dies after fewer than 200 rounds.

An improved flower pollination technique was proposed by Mittal et al. [12] to speed up threshold-sensitive energy-efficient clustering protocols in WSN. This was designed to keep the network stable for a lengthy period of time. Although the last node dies later in the proposed protocol, the first node dies earlier than in the previous models. Zaidi and Parma [13] presented the energy-aware trust-based gravitational search method in WSN to save energy, increase network security and reduce computing overhead. They recommended testing the ETGSA method in a WSN with numerous sink nodes grouped together. The GSA algorithm's main downside is that it takes an extended period for the optimal solution to arrive. It was proposed by Mehra et al. [14] that the remnant energy be set as an input to the Fuzzy Inference System in their Fuzzy-Based balanced cost CH Selection method (FBECS). Each node's Eligibility index has been assessed to determine the optimum CH. Through the selection of the best candidate for coordination in the cluster, the corresponding protocol has ensured load balancing in the cluster. This was only achievable if each sensor node's chance of detection was taken into account. As a final point, the results have confirmed the network's capacity to maintain its high data transmission rates while also increasing its overall lifespan.

Simulating the tree rotation clustering perfect, Priyadarshini and Sivakumar [15] were able to balance the load. The scientists have used a novel modified K-means clustering technique to break down the single big area network into a number of smaller clusters. By building two models, they've also reduced the computing load. A system known as Cluster Head (CH) assortment has also been implemented for determining the maximum number of sensor nodes covered. Finally, the experimental findings show that the developed model outperforms conventional methods when it comes to extending the network's lifespan. The biased tracking model, Zhang et al. 2019 [18] is built to eliminate the mismatching between the biased measurement and the unbiased tracking model and the differential processing is used in the biased tracking model, which can remove the high dynamic biases at the same time. The node degree of wireless communication is classified for disaster situations, and virtual routes are set according to the predetermined node degree. The routing method is employed with base stations as the infrastructure, such that a route may be assigned, maintained, and recovered which uses deep learning, and virtual routes are created by employing the Viterbi algorithm.

The hybrid robust-stochastic approach in order to get optimal offering and bidding strategies for a large industrial consumer, a new mathematical model is proposed. The uncertainties of load demand, power market prices, solar radiation, temperature and wind speed are taken into account in the proposed model by using a hybrid robust-stochastic approach (Jouhari et al. 2019) [19].It provides scalable, robust and energy-efficient routing. It is a position-based routing where the nodes close to the vector from the source to the destination forward the message. It also adopts localized and distributed self-adaptation algorithm as explained in Anuradha andSrivatsa (2019) [20].

Deep Learning-High Dynamic Biased Track (DL-HDBT) algorithm was introduced to identify best routing method. The DL-HDBT combines the deep learning and hybrid dynamic biased tracking algorithm. Deep learning (DL) helps in the identification of the best relay nodes in the network and traffic-congested nodes are tracked using a high dynamic bias track [21]. Convex directional flooding optimization (CDFO) algorithm was proposed to improve the latency, throughput, lifetime of the nodes in the network under thermohaline condition and longshore drift from longshore current, which consist of transportation of sediments [22]. A location aware opportunistic routing algorithm was introduced to analyse the main problems in under water communication; forwarding set selection forwarding set ranking to handle FSR problem, void handling method to handle the communication void (CV) and overhear and suppression procedure to deal with duplicate forwarding suppression (DFS) problems [23]. A novel underwater acoustic OFDM communication is introduced with the Polar Run Limited encoder (PRLE) scheme. PRLE encodes the data on the transmitter side and at the receiver side with the help of the codebook, the original information is retrieved. The main concept of FWFT is it reduces size and complexity in order to achieve a high-performance UW-OFDM system [24]. In this nominal, an innovative method called Gravitational Search Hybrid Hexagon-Deep Learning algorithm is proposed. By combining Deep Learning and

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Gravitation Search, the optimized weighting factor is determined after that which is given to ANN to classify the relay nodes [25].

Therefore, we addressed various important factors for CH selection in this study:

- The objective function increases the energy efficiency by including the fitness value (FV) for energy consumption.
- The objective function includes the FV for cover area to adjust the number of nodes covered by each CH.
- The protocol can be used even when all nodes have the same energy (initial state).
- Unnecessary operations are minimized by directly selecting nodes.
- The number of CHs can be controlled and predicted.

3. PROPOSED SCHEME

In this section, how the optimal CH is selected by using the proposed model is explained deeply. Before that, the system model along with the objective function is defined in this work.

3.1. Network model

Sensor nodes make up a large portion of WSNs. These nodes can be located across the network, where they are responsible for routing data to sink nodes. Each node in the cluster uses more energy because of the large distance between the sensors and the base station. This has an impact on the network's lifespan. The network's lifespan can be increased by preserving energy, having more active nodes, and reducing delay. When transmitting data to the sink node, optimum cluster heads use the least amount of power possible to save node energy. Consider a WSN with nC clusters, each of which is referred to as cl i, where I ranges from 1 to n. There is a node named D ij that can be found in any of the current clusters, where i=1,2,...L and j=1,2,.....> The cluster head, i.e., CH i," is selected among the remaining cluster nodes and assumes leadership of the cluster as a whole. The energy, the distance between nodes, and the packet delay are all taken into account while picking a CH. Only the CH connects straight with the base station B s. To extend the network's lifespan, this study offers a MWOA for selecting the best CH based on a diversity of factors, such as distance and energy consumption.

3.2. Energy Model

fs and mp are the only two scenarios that this model recognises (MP). Free space model d(2)powerless is utilised when the distance between a transmitting node and receiving node is less than the threshold d 0. Otherwise, the d(4)powerless multipath model is employed. A k-bit packet across a distance d can be calculated using Equation (1), which is based on the two models above.

$$E_{Tx}(K,d) = E_{elec} * K + \varepsilon_{fs} * k * d^2, d < d_0$$
$$E_{Tx}(K,d) = E_{elec} * K + \varepsilon_{mp} * k * d^4, d \geq d_0 \tag{1}$$

Electronic circuits consume energy called E elec when processing 1-bit data. The energy required to transmit one bit of data in the free-space model and multipath model, correspondingly, is known as _fs and _mp. They are affected by the transmission's overall length. Notice how d2 and d(4) relate to the amount of energy dissipated in free space and via multipath. By using Equation, d 0 can be determined (2):

$$d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}} \tag{2}$$

A k-bit message's transmission energy is determined in Equation (3):

$$E_{Rx} = E_{elec} * K \tag{3}$$

3.3. Distance Model

According to Eq. (4), it is possible to calculate the mathematical model of distance parameter fdist (q), which determines the distance between a normal node (as well as between the CH and the CH and the BS) and between two normal nodes (as well as between two normal nodes) (6). You're looking for a number between [0, 1] for fdist (q).

$$f^{dist} = \frac{f^{dist}(q)}{f^{dist}(p)} \tag{4}$$

$$f^{dist}(q) = \sum_{i=1}^{L} \sum_{j=1}^{M} \left\| D_i - CH_j \right\| + \|CH_j - B_s\| \tag{5}$$

$$f^{dist}(p) = \sum_{i=1}^{L} \sum_{j=1}^{M} \|D_i - D_j\| \tag{6}$$

3.4. Proposed K-Means Scheme:

Clusters are formed when the sensor nodes have been deployed in the sensed region. This reduces the quantity of information that needs to be sent back and forth between nodes, hence reducing the overall transmission load on the base station.

In this part, we'll explain how we plan to do things. K-means method is used to create clusters from nodes based on Euclidean distance between each other in the suggested scheme. Inputs to the method include sensor nodes with position information and the k number of clusters they belong to. There are a total of k clusters in the output: C= c1, c2,... ck.

Using K-means, there are three steps to the process.

Step 1: Early clustering

In wireless sensor networks, the K-means algorithm is used to create clusters. The first step is to randomly select k out of n nodes as CHS. According to distance, each of the residual nodes chooses its closest CH.

Step 2: Re-clustering

Next, each node in the network is given a cluster identification. Equation illustrates the centroid of each cluster (7).

$$Centroid(X,Y) = \left(\frac{1}{s}\sum_{i=1}^{s} x_i , \frac{1}{s}\sum_{i=1}^{s} y_i\right) \quad (7)$$

You should be aware that a cluster's centroid is a virtual node positioned in the middle. During this stage, the cluster centre is changed and the new centre is the average location point of all sensor nodes in the cluster. All cluster centres (CHS) are recalculated and re-allocated for each node using Euclidean distance for each cluster. Step 2 is iteratively executed until no points switch clusters and CHS are no longer changing.

Step 3: Selecting CH

Cluster ID numbers are allocated to each node in a cluster based on its distance from the centroid, assigning a lesser amount to the closer one. The order in which nodes are selected as CHS is indicated by their ID numbers. As a result, selecting a node as CH is heavily reliant on the ID number. Every round, the CH's leftover energy is verified to ensure the network's connectivity. After a predetermined threshold, the next node is chosen as a new CH if its energy falls below that threshold. All other nodes are notified by the newly chosen CH of this change in the CH. The proposed approach uses multihop transmission between CHS and BSs by employing a MWOA for selecting the best path in each round of clustering and CH selection.

3.5. **Whale optimization algorithm**

The WOA mimics the humpback whale's foraging activity in order to build the algorithm. A random set of solutions is generated at the beginning of WOA's execution mechanism, as is the case with other population-based algorithms. Searching the prey, encircling the prey, and launching a spiral bubble-net attack are the three main stages of WOA's search method. In order to strike a balance between exploratory and exploitative processes, WOA makes use of these three strategies. When a pre-determined criterion is met and the optimization results are generated, the search operation concludes.

Step 1: Searching the prey phase

Based on their current location, whales conduct a haphazard search for the target in the search space. For the sake of learning more about the search area, the programme makes use of the whales' food-finding mechanism. This behavior's mathematical formulation is provided by:

$$\bar{D}_{is} = |C.S_{rnd}^{(t)} - S^{(t)}| \quad (8)$$

$$S^{(t+1)} = S_{rnd}^{(t)} - A.\bar{D}_{is} \quad (9)$$

A random solution, S rnd, is picked from among the current solutions, and t denotes how many iterations have been performed so far. Dis is the distance between the current solution and random. Multiplying elements one at a time is referred to as (.), and the symbol || denotes absolute value.

Equations (8) and (9) use parameters A and C, which are referred to as co-efficient vectors.

$$A = 2a_1 \times rnd - a_1 \quad (10)$$

$$C = 2 \times rnd \quad (11)$$

As each iteration progresses, a 1 decreases linearly from two to zero, and rnd is a random value between 0 and 1.

Step 2: Encircling the prey

In order to maximise profits, the algorithm uses this whale-hunting strategy. During this phase, the optimum option is likely to be the one that is closest to the ideal value. Alternate options put up by the general public shift the current best choice. The mathematical expressions used to describe this behaviour are listed below:

$$\bar{D}_{is} = |C.S_{best}^{(t)} - S^{(t)}| \quad (12)$$

$$S^{(t+1)} = S_{best}^{(t)} - A.\bar{D}_{is} \quad (13)$$

Where S best is the best solution based on the whales' FVs up to the current iteration, S best.

Step 3: Bubble-net attack

Humpback whales use a bubble path in the shape of a spiral to get close to their prey. Using a bubble-net attack, you can narrow your search to a specific area nearby. Here's how the bubble-net process is done in practise:

$$D^* = |S_{best}^{(t)} - S^{(t)}| \tag{14}$$

$$S^{(t+!)} = D^*.e^{bl}.\cos(2\pi l) + S_{best}^{(t)} \tag{15}$$

The logarithmic spiral path's shape, b, is fixed, and the random integer l is derived from the equation below:

$$l = (a_2 - 1)rnd + 1 \tag{16}$$

If you look at Eqn. (16), the value of a 2 declines linearly with each iteration, from (-1) to (-2) and rnd[0,1].

When moving from algorithm exploration to algorithm exploitation, the coefficient parameter A is used. Equations (8) and Eqn. (9) begin the global search when |A|1, indicating that the exploratory process has been selected (9). Based on a constant probability value a (a=0.5), if |A|1 the possible whale upgrading position by Eqn. (13) or Eqn. (15) is determined, the search process shifts between prey-encircling and bubble-net assaulting strategies. It's possible to see a mathematical version of this here.

$$\begin{cases} S^{(t+1)} = S_{best}^{t} - A.\overline{D}_{is} & if\ a < 0.5 \\ S^{(t+1)} = D^* e^{bl}\cos(2\pi l) + S_{best}^{t} & if\ a \geq 0.5 \end{cases}$$

(17

3.6.1. **Proposed modified WOA**

Humpback whale hunting patterns were the inspiration for the whale optimization method. This phase of the whales' migration has been termed the "random solution phase" due to the fact that a random solution is used by the entire population. The global search phase of the algorithm served as a reference for this step. Local searches were conducted using the whale's bubble-net attack method and encircling the target. The best value was utilised to update the solutions in both phases. Using the A and C vectors of co-efficients, we deviate from the original answer. There is a new selection parameter in the proposed model that ranges from 1 to 0 in the standard WOA model. The value of is used to select between the exploration and exploitation stages. The usual WOA parameters A and b have also been updated. Subtracting an arbitrary number from A yields the value. The bubble-net approach of searching for life in outer space utilises this value rather than 1 as in WOA. The answer is right here:

$$\beta = 1 - iter/maxiter \tag{18}$$

For example, if you want to know how many iterations you have left, you can use the following equation.

Starting with a random population, MWOA follows the same pattern as other metaheuristic algorithms. The exploration phase is selected if the value of is more than a random sum and another random sum is less than 0.5. The current solution, in contrast to the WOA's hunt for prey phase, is renewed to enhance exploration. Alternatively, the surrounding prey phase in Equation (13) is employed. In WOA, the population surrounding the best value of b is taken from [-1,1] instead of 1, hence the value of A can only be in the range [-1,1]. As soon as a solution is updated in an iteration, the population is estimated using the formula in Eqn (19).

$$New_{pop} = round\{\left(\frac{minpop - pop}{maxnfes}\right) * nfes + pop\} \tag{19}$$

When solving Eqn. (19), the population value pop is represented by pop, and the population value minpop is represented by minpop. If you want to evaluate as many functions as possible, you can do it as many times as you like. We've set the minimum pop count to 15 while we explore. A reduction in population reduces the algorithm's complexity and improves its capacity to find solutions locally. Returning the best FV, the output is returned. Following is a step-by-step breakdown of how the proposed concept would be implemented:

1 The random population and other relevant parameters should be set to a random value.

2 Evaluate each possible solution's fitness, and then select the one that is now the most fit and most effective.

3 The traversal parameter must be determined at this step.

4. Determine the most recent values for A, C, b, and l.

Reinitialize the existing solution if A is greater than a random number and that random value.

5 The encircling prey technique should be used if A is bigger than a random number and the random value is less than or equal to 0.5.

6 The bubble-net attack method should be used if A is less than or equal to a random number.

7 Using either step 5, step 6, or step 7, each solution in the population can be updated.

8 Use equation to calculate the new population's value after the reduction (19)

9 For as long as the termination complaint is not met, you can go between steps 2 and 9.

10 It's time to output your greatest fit and the best solution.

Figure 1 depicts an example in which there are four clusters, each with a single BS. All CHS and BS were measured in terms of their distance. BS is always at the base of the tree. The distance between CHS, CH, and BS is used to measure the weight between nodes in the network. Each CH delivered packets to the CH or straight to the BS after generating the minimal spanning tree using the MWOA method.

4. RESULTS AND DISCUSSION

The projected method has been realised in MATLAB R2018a with NVIDIA Tesla K80 GPU with 4 GB of RAM. The implementation proposed architecture is defined in the figure.1.

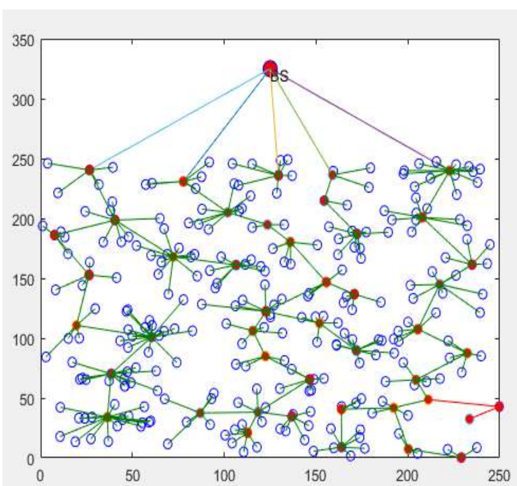

Figure 1: Proposed Implemented Network Architecture.

Here, we consider a network of 300 and 600 sensor nodes randomly distributed in a field of 250m * 250m, and the values used in the first model are described in Table 1.

Table 1. Simulation Parameters

Parameter	Value
initial energy of nodes	1 J
Eelec	50 nJ/bit
Position of base station	0 m*0 m
Ecpu	7 nJ/bit
Ɛfs	10 pj/bit/m2
Ɛmp	0.0013 pj/bit/m4
Size of the network	250 m*250 m
N (Number of deployed nodes)	300 and 600
Packet size	4000 bits

4.1 Performance metrics

4.1.1. Network lifetime

The network's lifespan is measured in cycles till the machine's demise. First Node Death (FND) and Last Node Death (LND) were used to measure the network's lifetime during the simulation because the data collector nodes' fields are no longer monitored if a node dies during the data collection procedure. LND shows the ratio of dead nodes to active nodes. For 5000 rounds with 500 sensor nodes, the network's lifespan increases as energy usage climb.

4.1.2. Energy consumption

The algorithm's power efficiency can be gauged by looking at how much energy it uses in a given round. In order to determine the battery's remaining energy, the cumulative quantity of energy must be calculated (in joules).

4.1.3. Network throughput

BS receives an estimated amount of useful data based on network performance. As a result, the effectiveness of a routing algorithm may be evaluated by looking at its network performance.

4.2. Evaluation of proposed System with 300 nodes

In this section, the proposed model is compared with recent year technique called rat algorithm [16] and jellyfish algorithm [17]. Since, these algorithms are new, which is not used in the WSN network for optimal CH selection. Hence, these two existing techniques are implemented with proposed model for validation process, but the MWOA algorithm provides better results. The jellyfish algorithm requires only two control parameters, where rat algorithm has different mutation strategy. Here, two set of experiments are carried out by considering 300 nodes as first experiments and 600 nodes as second experiments. Figure 2 to 6 presents the graphical analysis of proposed perfect in terms of throughput,

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alive nodes, dead nodes, total packets sent and energy consumption.

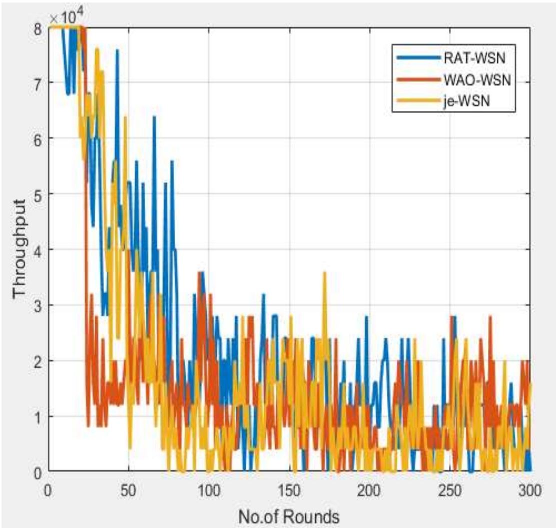

Figure 2: Graphical Representation of Proposed Model in terms of Throughput

In this above analysis, the throughput performance for all algorithms is average only. Because, the WOA is modified with population reduction.

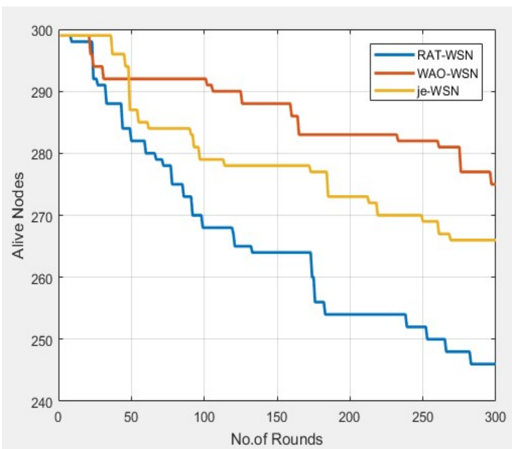

Figure 3: Graphical Representation of Proposed Model in terms of Alive Nodes

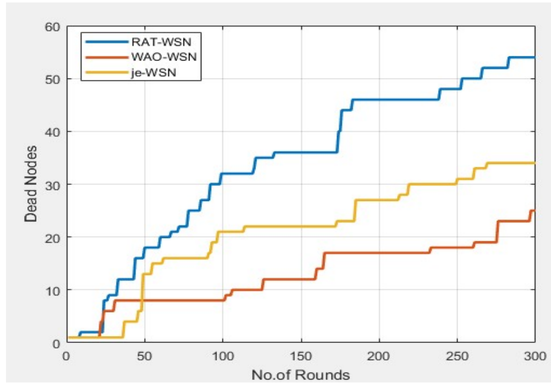

Figure 4: Graphical Illustration of Proposed Ideal in terms of Dead Nodes

The first node death is used to determine scalability after the number of rounds per scheme has been determined. In order to disclose the stability of the proposed structure, total electricity of the signalled network is calculated over several sensor nodes. By ensuring an optimized network life and residual energy, the proposed optimizing approach outperforms than rat and jelly fish algorithm.

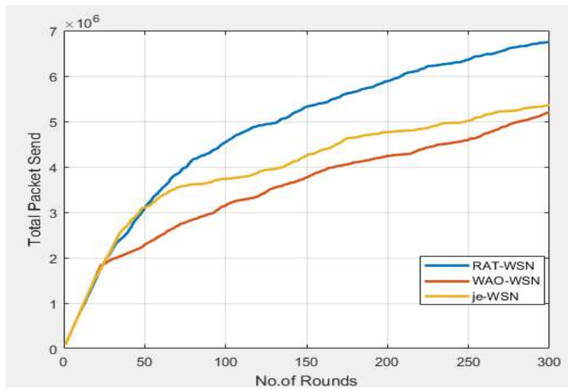

Figure 5: Graphical Representation of Proposed Model in terms of Total Packet Sent

Scalability refers to the ability to make changes to a large number of nodes at once, something that may not have been anticipated during the network's initial implementation. The major challenge in the design of such networks is how to handle an adequate amount of extra SN without redesigning the entire network. Network scalability is an important consideration while designing routing methods for WSN.

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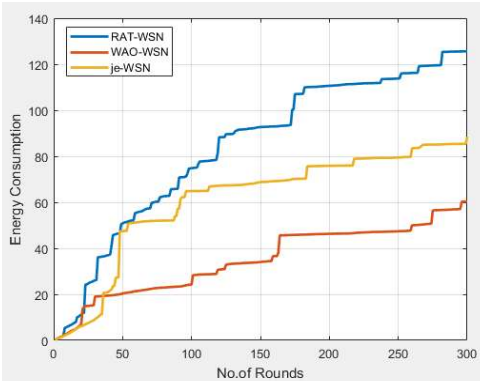

Figure 6: Graphical Illustration of Proposed Ideal in terms of Energy Consumption

The packet is delivered quickly and saves 45 percent simulation time with the proposed routing protocol and energy is lower than the non-optimization protocol, since the CH selection is better for the proposed routing and the best contact knot with more energy is selected. The above figures show that the energy used by the proposed optimized routing algorithm is less than the energy used by the proposed route protocol with MWOA.

4.3. Evaluation of proposed System with 600 nodes

In these experiments, the analysis is performed at high iteration (i.e.600) with 600 nodes, in relation to numerous parameters such as energy consumption, throughput, dead nodes, live nodes and total packet sent by considering the proposed model with RAT and jelly fish technique. Graphical representation of proposed model with existing techniques by varying nodes for different metrics is given in Figure 7 to 11.

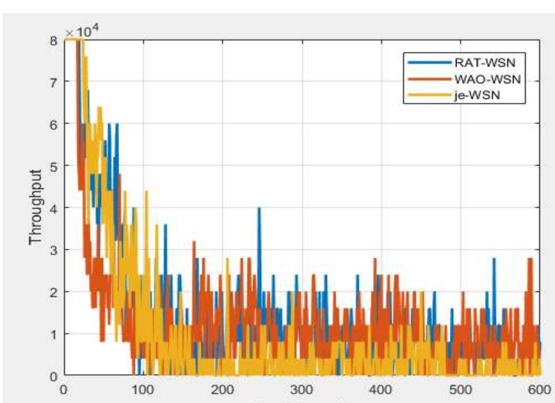

Figure 7: Graphical Demonstration of Proposed in terms of Throughput by varying no. of nodes

Even at high iteration, all the techniques has high throughput and the proposed model easily falls into local and global optimum that requires more modification for better performance. The results of MWOA are not upto the expectation levels. This must be improved by choosing the proper initialization or weights that plays a major role to achieve better performance.

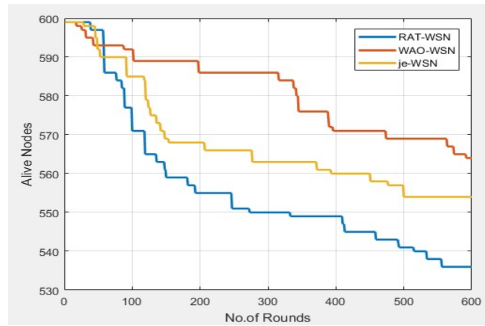

Figure 8: Graphical Representation of Proposed Model in terms of alive nodes by changing no. of nodes

While comparing with the existing techniques, the WOA has high alive and its starts to reduce gradually even at 500 iterations. But, the RAT has less sum of alive nodes, when the number of iterations is increased. This shows that the performance of WOA is high.

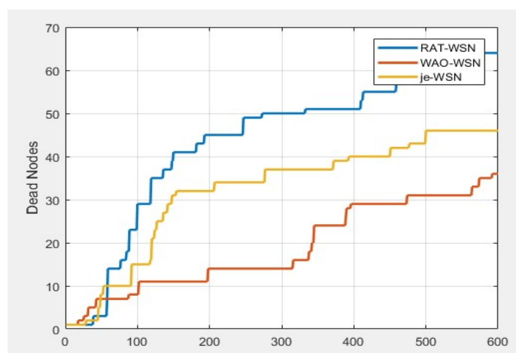

Figure 9: Graphical Representation of Proposed Model in terms of dead nodes by varying no. of nodes

While comparing with RAT and Jelly fish, the proposed model has fewer dead nodes, where RAT has high dead nodes after reaching 250 iterations. But, the Jelly fish has average dead nodes than both techniques.

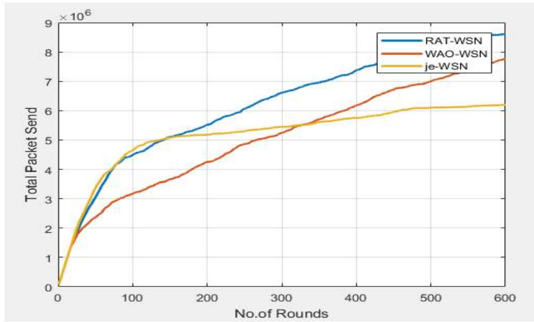

Figure 10: Graphical Representation of Proposed Model in terms of Total packet send by varying no. of nodes

When the energy for the network is high, more data are transmitted over the network. Therefore, the proposed WOA sent more data than the existing model. But the jelly fish algorithm slowly transmits the data after reaching the 150th iteration. While comparing with RAT, WOA has slightly less number of transmission and this is due to the reduction of more number of population in the algorithm. This must be improved in future work by modifying the proposed model.

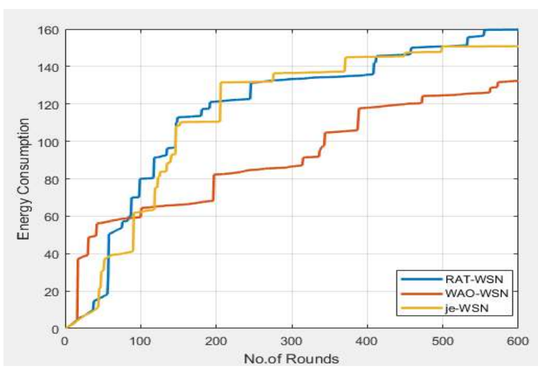

Figure 11: Graphical Representation of Proposed Model in terms of energy consumption by varying no. of nodes

In the above figure, it is clearly shown that the RAT and jelly fish has high energy consumption than the proposed model. The jelly fish has only two parameters such as population size and a number of iterations and this leads to high energy consumption.

5. CONCLUSION

WSN is plagued by significant energy constraints, one of the most difficult difficulties. Each cluster's centre serves as a data collection site for this investigation. For data collection, a clustering algorithm known as K-means is used. Reduced inter-cluster communications and increased energy efficiency for sensor nodes can be achieved by using this method of inter-cluster communication. We came up with the MWOA as a way to help people figure out which route is best for them. MWOA determines the ideal solution based on two objective parameters: energy consumption and travel distance. A variety of factors and settings were simulated in order to determine the resilience of our strategy. As a result of these simulations, the suggested protocol has a longer network lifetime, lower energy usage, and is much more scalable than its predecessors, such as the Rat and the Jellyfish algorithms. However, the proposed model's throughput and total packet send between BS and CH are equal to those of the existing techniques.

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