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# Kinetic Gas Molecule Optimization based Cluster Head Selection Algorithm for minimizing the Energy Consumption in WSN

**S. Saritha[1], Dr. E. Sreenivasa Reddy[2]**
[1]Research Scholar, Dept. of Computer Science & Engineering,
Acharya Nagarjuna University,
Guntur, AP State, India
e-mail: sarithanune@gmail.com
[2]Professor, Dept. of Computer Science & Engineering
Acharya Nagarjuna University,
Guntur, AP State, India
e-mail: esreddy67@gmail.com

**Abstract**— As the amount of low-cost and low-power sensor nodes increases, so does the size of a wireless sensor network (WSN). Using self-organization, the sensor nodes all connect to one another to form a wireless network. Sensor gadgets are thought to be extremely difficult to recharge in unfavourable conditions. Moreover, network longevity, coverage area, scheduling, and data aggregation are the major issues of WSNs. Furthermore, the ability to extend the life of the network, as well as the dependability and scalability of sensor nodes' data transmissions, demonstrate the success of data aggregation. As a result, clustering methods are thought to be ideal for making the most efficient use of resources while also requiring less energy. All sensor nodes in a cluster communicate with each other via a cluster head (CH) node. Any clustering algorithm's primary responsibility in these situations is to select the ideal CH for solving the variety of limitations, such as minimising energy consumption and delay. Kinetic Gas Molecule Optimization (KGMO) is used in this paper to create a new model for selecting CH to improve network lifetime and energy. Gas molecule agents move through a search space in pursuit of an optimal solution while considering characteristics like energy, distance, and delay as objective functions. On average, the KGMO algorithm results in a 20% increase in network life expectancy and a 19.84% increase in energy stability compared to the traditional technique Bacterial Foraging Optimization Algorithm (BFO).

**Keywords**- Energy Consumption; Data Aggregation; Kinetic Gas Molecule Optimization; Network Lifetime.

## I. INTRODUCTION

Nodes in WSNs are used to collect and store environmental data. [1] Random or deterministic distributions of nodes in WSNs can be found. The nodes are scattered at random in areas that are problematic for people to admittance [2]. The number of nodes is large, however the initial charging of those nodes consumes very little energy. There are two major concerns that affect these networks: energy usage and network lifespan [3–5]. A base station (BS) receives the data from the nodes and processes it [6]. Single-hop or multi-hop data transfer can be used [7-9]. Forest fire detection, patient monitoring, and military traffic management are just a few of the many uses of WSN. Fault tolerance, scalability, prices, hardware restrictions, reliability, WSN topology, transmission situation, and energy consumption are some of the most important considerations in WSN design [10]. Clustering and routing [11-13] are two strategies for extending the lifespan of WSNs. Clustering is the primary focus of this study, rather than routing methods.

Clustering [14] is a strategy that divides a large geographic area into smaller, more manageable portions. Using it, the burden of sensor nodes can be distributed equally across all of the server nodes, with one of them being designated to function as the cluster's central hub (CH). For optimal information transfer, the choice of CH is critical. CH reformed during distinct iterations in order to provide the best results in practise. A CH with a superior amount of cluster members is part of the unique cluster. The CH is responsible for coordinating all of the cluster's nodes [15]. Figure 1 shows the process of clustering.

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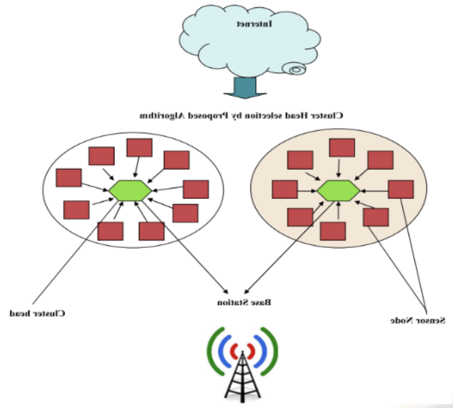

*Figure 1. Art of developed CH selection ideal.*

However, the network's energy efficiency ratio must be balanced by the right CH selection [16] and optimal capabilities. For this reason, as artificial bee colonies, artificial immune systems, and evolutionary algorithms are being utilised in the clustering process in an effort to circumvent the NP-hard optimization problem.

The routing protocol has a major issue when it comes to data transfer from the sensor node to the base station. Energy, time, distance, and so on can all be minimised with the use of an optimal CH selection framework In the WSN, most of the various algorithms were used to pick the best CH. These algorithms have made some contributions, and the results have demonstrated their amazing performance in finding the ideal CH. Algorithms like this one have a number of limitations, including a slow convergence rate and an inability to solve multi-objective problems. This research therefore provides a new CH selection approach for selecting an optimal CH in WSN to overcome these difficulties. GMO algorithms are used in this study to select the best CH for a long-term network performance improvement.

The repose of the paper is prearranged as: Section 2 provides the detailed study of existing techniques with its limitation. The brief explanation of proposed methodology for selection of CH along with system model is given in Section 3. The experimental analysis of proposed technique in terms of various parameters is described in Section 4. Finally, the conclusion of the research work with future development is presented in Section 5.

## II. RELATED WORKS

Kumar, M.M. [17] proposed a hybrid BFO and fruitfly optimisation algorithm (FOA) for energy efficient CH selection in wireless sensor network. The bacterial foraging optimisation algorithm is inspired by the group foraging behaviour of bacteria and moving away from specific signals. The FOA is simple framework and easy to implement for solving an optimisation problem with different characteristics. It is robust and fast algorithm and used to solve discrete optimisation problems. The simulation results show that the proposed method achieves better energy efficiency and network lifetime of 35%, 58%, and 67% compared to existing methods like ant colony optimisation, particle swarm optimisation and genetic algorithm. But, the CH selection is based on degree of node, residual form node energy, and the coverage ratio intra-cluster distance, where the proposed KGMO considered energy, distance and delay that shows effective results than BFO.

Alla, V.K. and Mallikarjuna, M., [18] implement a joint optimal clustering and routing solution using Type-2 Fuzzy Logic as well as BFO. In this work, the author proposed to design and implement an efficient cluster head selection algorithm using Type-2 Fuzzy Logic system and then use BFO routing algorithm to find optimal path for sending aggregated data to the BS. In the network, the hot-spot problem is minimized by reducing the over heads in the formation of cluster, and helps in reducing the consumption of energy thereby prolonging the Network Life Time. The results are compared with LEACH protocol and achieved better network life time, increased residual energy and lower packet delivery loss. However, the results proves there is a decrease in packet loss using this particular algorithm and it can be used for medium sized cluster and static BS. But, the proposed KGMO model effectively send the data packets without loss and KGMO is used for selecting the CH, where BFO is used for finding the optimal path for transmission.

Gupta, P. [19] designed variants of Optimized Hybrid energy-efficient distributed (OHEED) protocols named as HEED-1 Tier chaining (HEED1TC), HEED-2 Tier chaining (HEED2TC), ICHB-based OHEED-1 Tier chaining (ICOH1TC), ICHB based OHEED-2 Tier chaining (ICOH2TC), ICHB-FL based OHEED-1 Tier chaining (ICFLOH1TC), and ICHBFL-based OHEED-2 Tier chaining (ICFLOH2TC) protocols. In HEED1TC and HEED2TC protocols, we have used chain-based intra-cluster and inter-cluster communication in HEED, respectively, for even load balancing among sensor nodes and to avoid more work load on CHs. Furthermore, for appropriate cluster formation, minimizing CHs variation in consecutive rounds and reducing complex uncertainties, BFO algorithm is proposed. An intelligent CH selection based BFO (ICHB) algorithm for CH selection is used in ICOH1TC and ICOH2TC protocols. Likewise, in ICFLOH1TC and ICFLOH2TC protocols, novel fuzzy set of rules is used additionally for CH selection to resolve the hot spots problem, proper CH selection covering whole network, and maximizing the network lifetime to a great extent. Here, either fuzzy logic or BFO will be worked for CH selection that leads to high computation time and there is no other options/conditions used that which algorithm must be worked first for selection process.

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Dhondiyal, S.A., [20] presents evolutionary bacteria foraging optimization method, named as EBFO, which uses a fitness function to measure the combined energy of the all sensor nodes in the cluster to make sure overall energy of cluster lesser energy than combined energy. It provides better field placement and cluster head selection. The results show the improvement in the energy efficiency and routing process in WSN as compared to standard BFO. The major objective of this exploration is to enhance the directing procedure, where BFO is used for finding the measure of combined energy. But, in the proposed KGMO, it is used to find the best CH based on three parameters as objective function.

Rambabu, B., [21] designed a Hybrid Artificial Bee Colony and Bacterial Foraging Algorithm-based Optimized Clustering (HABC-BFA-OC) for achieving enhanced network lifetime in sensor networks. In this proposed HABC-BFA-OC technique, the benefits of BFO is included for improving the local search potential of ABC algorithm in order to attain maximum exploitation and exploration over the parameters considered for cluster head selection. The simulation experiments of the proposed HABC-BFA-OC technique confirmed an enhanced network lifetime with minimized energy consumptions during its investigation with a different number of sensor nodes. Here, BFO used as a part to improve the searching potential of ABC, where KGMO is used as single optimization algorithm for selecting the CH.

Gupta, P. [22] explores the capabilities of Intelligent cluster head selection based on bacterial foraging optimization (ICHB) algorithm and fuzzy logic system (FLS) for searching better cluster head (CH) nodes without using any randomized algorithms in the network. In this paper, the clustering procedures of ICHB-HEED is further improved by applying the combination of ICHB algorithm and FLS system based on residual energy, node density and distance to base station (BS) parameters which results in ICHB-Fuzzy Logic based HEED (ICFL-HEED) protocol. It alleviates the formation of holes and hot-spots in the network, delays the death of sensor nodes (SNs), minimizes the energy consumption of SNs, forms even-sized clusters and extends the network lifetime competently. The delay parameter is not considered in this work as objective function.

Deepa, S.R. and Rekha, D., [23] aimed to improve the network lifetime by organizing sensor nodes into clusters achieves this goal. Further, the nodes which do not join any cluster consume high energy in transmitting data to the base station and should be avoided. There is a need to optimize the cluster formation process by preventing these left-out nodes. BFO is used in this paper as an optimization method for improving the clustering performance in WSN by preventing left-out node’s formation. The performance of BFO is compared with the Particle Swarm Optimization (PSO) and LEACH. BFO is used only for prevention of left-out nodes and it is used for the selection of CH.

## III. PROPOSED SYSTEM

### A. *System Model*

Overall, there are a large amount of sensor nodes included inside the WSN system. Actively routing data to sink nodes, these nodes can be found in the network. The vast distance among the sensors and the base station increases the energy consumption of each node in the cluster, reducing 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 CHs use the least amount of power possible to save node energy. In this example, we assume that the WSN has nC clusters, with $i = 1, \dots nc$. There are currently I j, and D ij nodes in the existing clusters, with $i = 1,2, \dots L$ and $j = 1,2, \dots M$. The CH I of the cluster is designated as the leader of the remaining cluster nodes, and it is responsible for coordinating the cluster's operations. The energy, the distance between nodes, and the packet delay are all taken into account while picking a CH. Indirect communication between the CH and BS is only performed by the CH. In order to extend the network's lifespan, we provide a new hybrid optimization technique that takes into account a wide range of factors, including latency, distance, and energy.

### B. *OBJECTIVE FUNCTION*

To select the key WSN parameters, including as distance, latency, and energy, are used to effectively select the best CH for a given application. In addition, the QoS parameter is a key consideration for effective network performance in this proposed work. In fact, the network's performance improves if it has a high Quality of Service (QoS) and energy, as well as a low delay. As shown in Equation (1), b is the continuous that set the value to 0.3 in our proposed model. For example, in Eq. (3), the distance among a mutual node and the base station is represented by $||D\ r - B\ s\ ||$, while in Eq. (2) it is represented by 1..

$$Objective\ Function\ (OF) = \beta \times f^2 + (1-\beta) f^1; 0 < \beta < 1 \quad (1)$$

$$f^1 = \gamma^1 * f_i^{dist} + \gamma^2 * f_i^{energy} + \gamma^3 * f_i^{delay} \quad (2)$$

$$f^2 = \frac{1}{n^c} \sum_{r=1}^{n^c} ||D_r - B_s|| \quad (3)$$

### C. *Parameter assessment in proposed CH selection model*

The parameters which exactly distinct in this work is modelled as follows:

1) *Energy:*

*In Eq.,(4) the amount of energy used by the WSN is specified. EN(D i) signifies the energy of the normal node, while EN(CH j) denotes the energy of each CH. Eq.(5) presents the f-energy(q), which is the energy that flows among the normal node and the CH, as well as among the CH and the network's BS, while the normal node and the CH are both active. Eq (6) presents the energy between normal nodes and CH, where the f-energy (p) between two nodes is provided in Eq. (7).*

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

$$f^{\text{energy}}(q) = \sum_{j=1}^{M} uEN(j) \tag{5}$$

$$uEN(j) = \sum_{\substack{i=1 \\ i\in j}}^{L} \left(1 - ED(D_i) * EN(CH_j)\right); 0 \le j \le M \tag{6}$$

$$f^{\text{energy}}(p) = M * \underset{i=1}{\overset{L}{Max}} \left(EN(D_i)\right) * \underset{j=1}{\overset{M}{Max}} (EN(CH_j)) \tag{7}$$

2) *Distance:*

*Eq. (9) defines the distance among the CH and the network's BS; $f^{dist}(q)$specifies the distance among two normal nodes; and $f^{dist}(p)$stipulates the distance between two normal nodes.*

$$f^{\text{dist}} = \frac{f^{\text{dist}}(q)}{f^{\text{dist}}(p)} \tag{8}$$

$$f^{\text{dist}}(q) = \sum_{i=1}^{L} \sum_{j=1}^{M} \left|\left|D_i - CH_j\right|\right| + ||CH_j - B_s|| \tag{9}$$

$$f^{\text{dist}}(p) = \sum_{i=1}^{L} \sum_{j=1}^{M} \left|\left|D_i - D_j\right|\right| \tag{10}$$

3) *Delay:*

*Here, it specifies that the data transmission delays for each node shall be within a range from [0, 1]. The delay is reduced significantly when the amount of nodes in a cluster is reduced. Total node count in Eq. (11), which is used to represent CH in WSN, serves as a denominator in Eq. (11).*

$$f^{\text{delay}} = \frac{\underset{j=1}{\overset{M}{Max}}(CH_j)}{L} \tag{11}$$

Choosing the best CH for the network is the major contribution of this study. This study offers a KGMO optimization technique in order to find the best one, as seen below:

### D. *Brief Description of KGMO*

An overview of the fundamental ideas of gas molecule rules that underlie the suggested algorithm is provided here. The ideal gas rule is given by [24] in order to use the suggested KGMO to determine the optimal solution for Eq. (1):

$$PV = NkT \tag{12}$$

In this equation, P is the gas pressure, V is the container volume, and N is the gas particle number.

The kinetic energy equation is resulting as:

$$\Delta k = w = F\Delta S = ma\Delta s \tag{13}$$

What we're looking at here is how much kinetic energy is lost in the transition between old and new places, how much work energy was consumed, how much Newton force was exerted, and how much difference there is between where the molecules were before and after this transition.

It is necessary to know the position, energy, (agent) while working with the KGMO model. Each gas molecule's velocity and position are determined by its kinetic energy. Gas molecules in the algorithm search the entire search space in quest of the coldest spot. Following that, consider a network with N agents (gas molecules). The ith agent's role is outlined in these terms:

$$X_i = \left(X_i^1, \dots . X_i^d, \dots . X_i^n\right), \ for\ (i = 1,2, \dots N) \tag{14}$$

where $X_i^d$ signifies the position of the ith agent in the dth dimension.

The velocity of the ith agent is accessible by

$$V_i = \left(v_i^1, \dots . v_i^d, \dots ., v_i^n\right), \ for\ (i = 1,2, \dots N) \tag{15}$$

Where $v_i^d$ represents the velocity of the ith agent in the dth dimension.

The Boltzmann distribution [24] governs the cylinder's gas molecule movement, which means that the velocities are proportional to the exponential of the kinetic of the molecules. An example of kinetic energy is the movement of an object.

$$k_i^d(t) = \frac{3}{2} NbT_i^d(t), K_i = \left(k_i^1, \dots k_i^d, \dots, k_i^n\right)\ for\ (i = 1,2, \dots N) \tag{16}$$

b is a constant, and N is the number of gas molecules, T id (t) is the temperature it in dth dimension at t is T.

The molecule's velocity is constantly being updated.

$$v_i^d(t+1) = T_i^d(t) w v_i^d(t) + C_1 rand_i(t) \left(gbest^d - x_i^d(t)\right) + C_2 rand_i(t)(pbest_i^d(t) - x_i^d(t)) \tag{17}$$

Because of the exponential decay of the covering molecules, T id (t) is computed as

$$T_i^d(t) = 0.95 \times T_i^d(t-1) \tag{18}$$

For each gas molecule, the best previous position in the container is represented by (pbest I i1,..., pbest I i n) and (gbest I i I n) is the best preceding position in the container. Random vectors are used to generate the initial values for each particle's velocity and position. The gas molecules' maximum and minimum velocities are represented here by [-v min,v max]. A gas molecule's resistance to slowing down can be expressed in terms of its inertia weight, w, which is the sum of the inertia weights of all its molecules. As an added bonus, a uniform random variable in the range [0,1] at time t is employed as part of the search process as well as rand i (t). Acceleration constants C 1 and C 2 are two.

It is assumed that the container contains only one kind of gas at any given time, therefore the mass m of every gas molecule is a random number among 0 and 1; once recognised, it remains constant throughout the procedure. Use of random numbers allows for several sorts of gas simulations inside a single algorithmic run.

The molecule's position is defined by the equations of motion in physics (19).

$$X_{t+1}^i = \frac{1}{2} a_i^d(t+1)t^2 + v_i^d(t+1) + X_i^d(t) \tag{19}$$

$a_i^d$ denotes the ith agent's acceleration in dth dimensions, and We may derive the acceleration equation from the formula.

$$a_i^d = \frac{dv_i^d}{dt} \tag{20}$$

On the other hand, the gas molecule laws, we have

$$dk_d^i = \frac{1}{2}m(dv_i^2)^2 \Rightarrow dv_i^d = \sqrt{\frac{2(dk_i^d)}{m}} \tag{21}$$

Therefore, from Eqs. (20) and (21), the acceleration is distinct as

$$a_i^d = \frac{\sqrt{\frac{2(dk_i^d)}{m}}}{dt} \tag{22}$$

Eq. (22) can be rephrased in the time interval t as

$$a_i^d = \frac{\sqrt{\frac{2(\Delta k_i^d)}{m}}}{\Delta t} \tag{23}$$

Thus, in a Acceleration would be measured in terms of units of time

$$a_d^i = \frac{\sqrt{2(dk_i^d)}}{\Delta t} \tag{24}$$

Then, from Eqs. (19) and (24), the position of the molecular is intended by

$$X_{t+1}^i = \frac{1}{2}a_i^d(t+1)\Delta t^2 + v_i^d(t+1)\Delta t + X_i^d(t) \Rightarrow$$

$$X_{t+1}^i = \frac{1}{2}\sqrt{\frac{2(\Delta k_i^d)}{m}(t+1)\Delta t^2 + v_i^d(t+1)\Delta t + X_i^d(t)} \tag{25}$$

Because each molecule mass (m) in an execution is a random value, the position is efficient for each unit time interval by m.

$$X_{t+1}^i = \frac{1}{2}\sqrt{\frac{2(\Delta k_i^d)}{m}(t+1) + v_i^d(t+1)X_i^d(t)} \tag{26}$$

The least fitness function by using

$$\begin{aligned} pbest_i &= f(X_i), \quad if\ f(X_i) \prec f(pbest_i) \\ gbest &= f(X_i), \quad if\ f(X_i) \prec (gbest) \end{aligned} \tag{27}$$

By using the distances between the current location and the best possible position and the best possible position, each gas molecule stabs to change its position "X"id". It is possible to derive the four parameters' ideal values from this.

## IV. RESULTS AND DISCUSSION

Matlab 2017 was used to test out KGMO-based CH selection for WSN network models. The nodes were spread out over a 350m × 250m space, with BS in the middle. The network's starting energy is 0.5 pJ/bit/m2 and the free space model's is 10pJ/bit/m2. Epower is set to 0:0013/pJ/bit/m2, Etr is set to 50nJ/bit/m2, and EDa is set to 5nJ/bit/signal for data aggregation. With 5000 rounds and 500 sensor nodes, the newly designed CH selection was tested. Figure 2 shows the network architecture created by the proposed model.

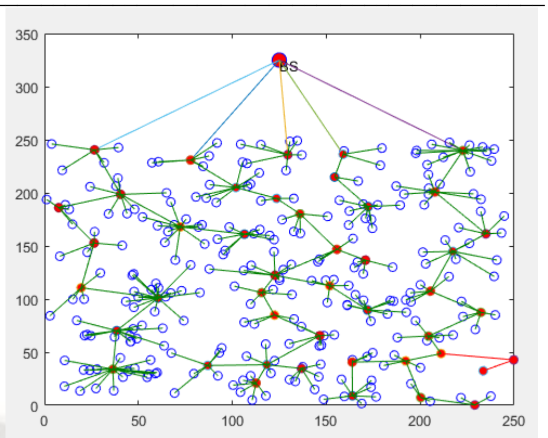


Fig.2. Proposed Implemented Network architecture.

### *A. Performance metrics*

#### *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 climbs.

#### *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).

#### *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.

### *B. Performance Analysis of Proposed KGMO model with 300 nodes*

In these experiments, the analysis is performed at low iteration (i.e.300), in relation to various parameters such as energy consumption, throughput, dead nodes, live nodes and total packet sent by considering proposed model with BFO [17-23] technique. The drawback of each existing technique is mentioned in Section 2, hence it is implemented with KGMO for validation process. Initially, the proposed model validation is checked by means of low energy consumption, total packet sending, total amount of dead nodes, total amount of live nodes, and throughput, as shown in Figure 3-7.

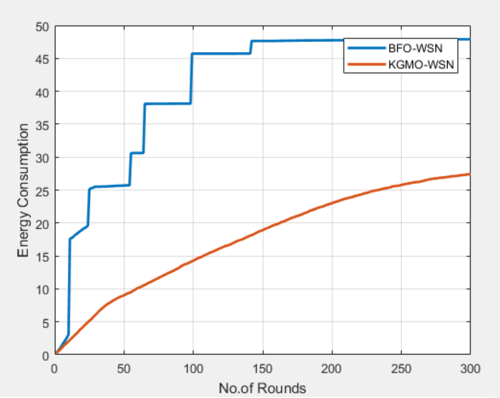


Fig.3. Energy consumption.

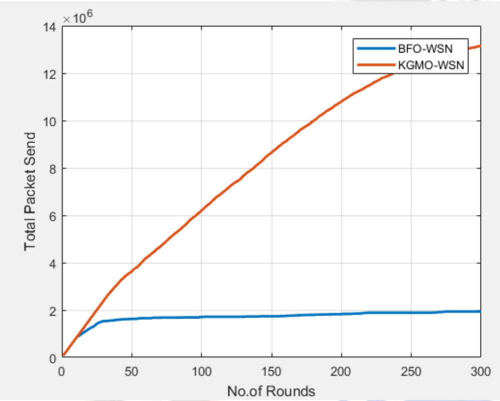


Fig.4. Total packets sent.

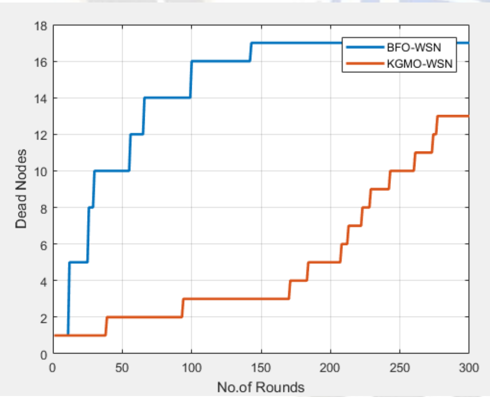


Fig.5. Dead nodes.

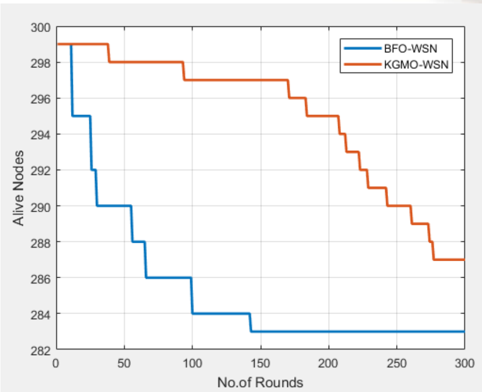


Fig.6. Alive Nodes.

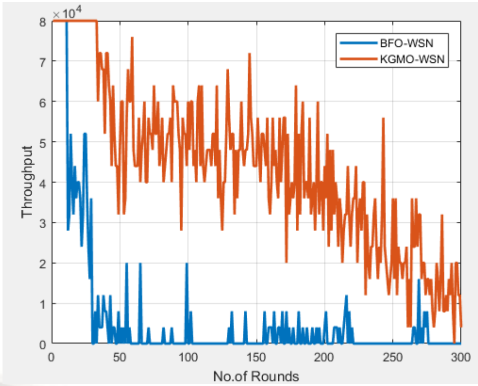


Fig.7. Throughput.

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. 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. To evaluate the process' s scalability, the number of SN nodes will be increased from 100 to 500, but all other design parameters will remain the same as in the test bed displayed. Fig. 2 depicts the amount of energy needed to move data from one place to another. 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. 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 BFO algorithm. While comparing with the existing technique, the total packet sent is high, dead nodes are less upto 150 rounds, alive nodes are also high initially. But, when the number of rounds increased upto 200, the proposed KGMO starts to degrades its performance by losing the alive nodes in the network. Increased throughput increased the performance of the KGMO, which is clearly shown in the graphical results. The next section validates the KGMO's performance by increasing the node with more number of iterations.

### C. Performance Analysis of Proposed KGMO model with 600 nodes

In these experiments, the analysis is performed at high iteration (i.e.600) with 600 nodes, in relation to various parameters such as energy consumption, throughput, dead nodes, live nodes and total packet sent by considering proposed model with BFO technique. Figure 8-12 shows the graphical representation of the performance of KGMO with existing technique.

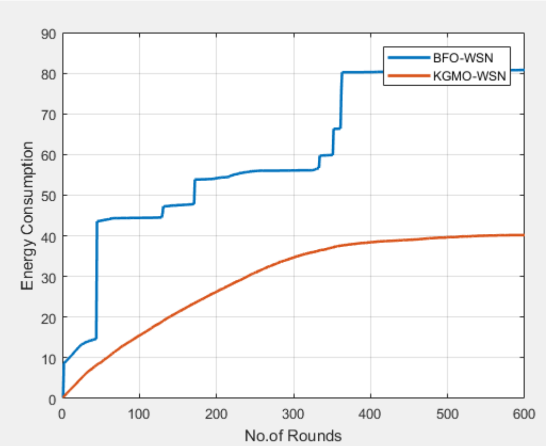


Fig.8. Energy consumption.

In the above figure, it is clearly shows that the BFO has high energy consumption than the proposed model. In BFO, the balance between exploration and exploitation is difficult due to the fixed step size and moreover, the local optimum is achieved early due to the weak communication in BFO.

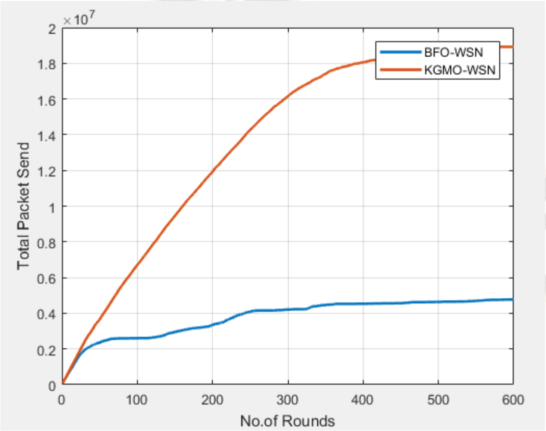


Fig.9. Total number of pockets sent.

When the energy is high, more number of data are transmitted over the network. Therefore, the KGMO sent more number of data than the BFO model.

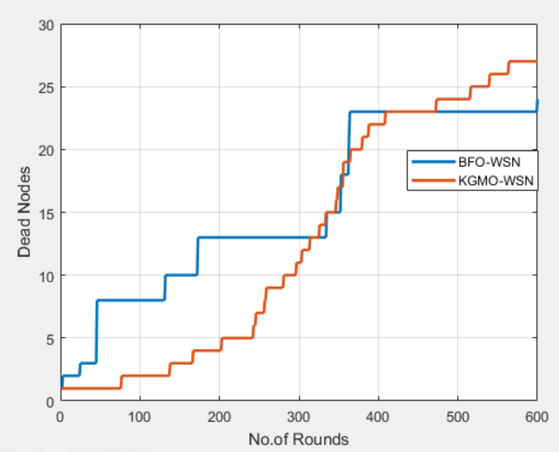


Fig.10. Dead Nodes.

When the number of rounds reaches 400, the dead nodes for BFO is stable, but the dead node is slightly higher in the proposed KGMO model and this is due to the weight of the gas molecules, which is easily falls into the local optimum.

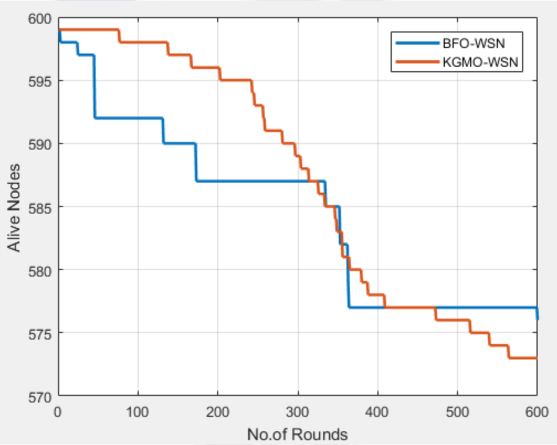


Fig.11. Alive Nodes.

While comparing with the BFO, the KGMO has high alive even at 600 iterations. But, the BFO has stable nodes when it reaches 350 rounds. This shows that the performance of KGMO is high.

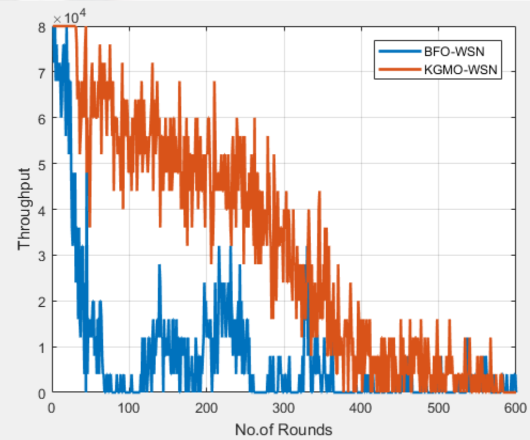


Fig.12. Throughput.

Even at high iteration, the proposed KGMO has high throughput than the BFO. However, the results of KGMO are not upto the expectation levels. This must be improved by choosing the proper inertia weight that plays a major role to solve the local optimum issues.

## V. CONCLUSION

WSNs include a large amount of low-cost, miniature sensing nodes, scattered randomly within target area without a specific infrastructure, which are far removed from the human scope. Due to its various applications such as health tracking, smartphones, army, disaster management and other surveillance systems WSN are one of the most important technologies. Sensor nodes are generally used in large numbers which operate independently in harsh environments without surveillance. Due to limited resources, such as low battery power, these wireless nodes are grouped together for efficient communication. Clustering systems can be used to solve the energy conservation problem in WSN development. It has thus been proposed to advance the network's energy consumption and lifetime by using a revolutionary KGMO-based CH selection mechanism. The KGMO protocol enables sensing nodes to send data for BS through the most efficient routes with the least amount of energy consumption possible to extend the life of the network. The KGMO algorithm determines the optimal solution based on three objective parameters: delay, energy consumption, and distance. We ran simulations with a variety of factors and settings to see if our strategy would hold up under pressure. The proposed protocol's simulation results show that it improves network lifetime, reduces energy usage, and provides great scalability compared to existing protocols. KGMO delivers 20% more network life than a strategy without optimization for CH selection, according to the comprehensive results. KGMO uses random vectors to initialise the velocity and location of each particle that shows inertia mass mimics the gas molecules' resistance to impede its travel. Slow convergence of the optimization is caused by high inertia weight while low inertia weight causes local trapping. The selection of the proper inertia weight is essential for improved performance in the future.

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