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Hybridization of Energy Optimization Technique for Cluster Based Routing using Various Computational Intelligence Methods in WSN

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Abstract— Approaches in WSN technology has determined by opportunity of tiny and inexpensive sensor nodes with adequacy of sensing multiple kinds of information processing and wireless communication. Network lifetime and energy efficiency are major indexes of WSN. Several clustering techniques are intended to extend the network lifetime but whereas there is an issue of incompetent Cluster Head (CH) election. To overcome this issue, an Integration of Novel Memetic and Brain Storm Optimization approach with Levy Distribution (IoNM-BSOLyD) has been proposed for clustering using fitness function. In the meanwhile, election of CH is done by utilizing fitness function, which incorporates following amplitude such as energy, distance to adjacent nodes, distance to BS, and network load. After clustering, routing techniques decides the detecting and pursuing the route in WSN. In this proposed work, a Water Wave Optimization with Hill Climbing technique (WWO-HCg) is introduced for routing purpose. This proposed methodology deals with ternary QoS aspect such as network delay, energy consumption, packet delivery ratio, network lifetime and security to select optimal path and enhance QoS as well. This proposed protocol provides better performance result than other contemporary protocols**.**

Keywords- WSN; Clustering; Routing; QoS.

I. INTRODUCTION

Basically, Wireless Sensor Networks (WSNs) has been exposed as an framework-inferior scheme with inexpensive Sensor Nodes (SN) [1]. It is mainly used to observe climatic conditions. Large amount of SNs is regioned in a random manner to impress the anxious platform.

In addition, WSN plays a vital role for examining the environmental nature such as forestry fervor presence, medicinal knowledge, limit consideration, clever metropolises, and so on [2]. Generally, the SNs are manufactured by multiple sensors, micro controller, communication unit, and electricity supply [3].

The operation performed by the sensor unit is to screen the environmental region, gather information, and transmit into neighborhood SN via communication unit [4]. However, SN holds less amount of energy, frequency range, cache space, and execution ability.

Furthermore, there exists some common issues such as security, connectivity, fault tolerance, coverage range, arrangement, and localization problem [5]. Mostly, the SN is specified as an unattended one due to low battery level. Because the batteries can't be re-changeable or energized.

Inappropriately, the communication cost is expensive compared to sensing and the execution cost [6]. At times, when SN has low energy and becomes irreplaceable, the energy of the current SN will be dissipated efficiently. In WSN, energy efficiency is a major issue, that pretends the complete network performance. Therefore, components which are utilized for manufacturing the WSN protocols must be more exquisite with effective power and adjustable to various environmental states [7].

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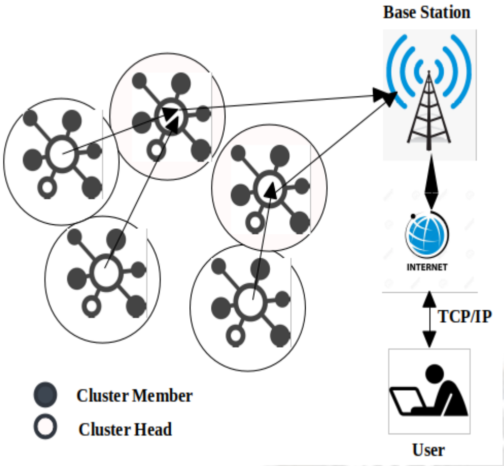

Figure 1.1 Basic Architecture of Clustering

Figure 1.1 illustrates the basic architecture of clustering. Various kinds of clustering and routing procedures are positioned for efficient enhancement of power in WSN [8]. In WSN, clustering is a familiar and significant technique, that segregates the network and gathers the neighborhood SNs as clusters.

Basic architecture of this clustering technique is illustrated in Figure 1.1. Here, the Cluster Head (CH) is selected from alternate SN, whereas rest of the nodes in the network is consider as the Cluster Members (CMs) [9]. Equivalent numeral of nodes in the system is termed as equivalent clustering and inadequate numeral of nodes in system is named as unequal clustering [10].

The CH is selected based on some specific constraints. Normally, the CH is performed in three phases as receiving information from CM, collect information from CM and transmit that to the MS node. In addition, the CH is considered as a relay node to transmit information to the MS node.

Dual optimization problems in WSN are clustering and routing. To solve this issue, an Integration of Novel Memetic and Brain Storm Optimization approach with Levy Distribution (IoNM-BSOLyD) is proposed for clustering using fitness function.

This proposed approach rends the fitness function for CH election utilizing with four constraints such as energy, distance to adjacent nodes, distance to BS, and network load. Moreover, proposed WWO-HCg approach is adapted for minimal path election to determine the inter-cluster paths to BS. Entire set of simulations are carried out to assure the energy-efficient performance of the proposed methodology.

Additionally, four clear quoted sections are systematized in this research work. Literature survey is dignified in section 2. The perfect workflow of the suggestion methodology is determined in section 3. The performance estimation is stated in section 4. The conclusion is crystal clear in Section 5.

II. Related Works

Few surveys are taken as reference to present this proposed methodology, which is shortly explained in this section.

Jian, et al presented the load balancing Rendezvous approach for efficient data collection in WSN. Here, packet communication routing continuity and model rendezvous preparation were defined for clustering. This t, Rendezvous Transmission Algorithm (RTA) was introduced to provide a best tradeoff among power preservation and traffic compensation. However, this control channel of the RTA might get congested [11].

Tarnaris, et al proposed enhancement of coverage region and area k-coverage by utilizing computational intelligence approach such as GA and PSO algorithms. However, the computational time was high, and the SN in WSN was distributed in asymmetrical manner [12].

Priya, et al introduced an adaptive power control and load balancing technique. The hybridization of TDMA/FD*MA technique has been utilized for load balancing technique. However, adaptive power control was facing an erratic disturbance [13].

Samad, et presented an effective technique for information collection in WSN with few obstacles. hierarchical agglomerative clustering and ACO approaches were used to create high-quality clusters at the existence of obstacles. An efficient tour creation technique was designed based on GA and multi-agent reinforcement learning. The main demerits of this research were stagnation phase, exploration, exploitation rate and convergence speed [14].

Menaria, et al proposed a new fault tolerance standard by utilizing AI to enhance the entire performance in WSN. It effectively handles the faults at node failure during data packet transmission to fault tolerance. However, lack of service availability has occurred due to breakdown in multiple systems [15]. Aghbari, et al reviewed optimization technique in WSN for routing. It provided complete instant of the previous research work in WSN field. This shows the routing path among the source and the destination [16].

Jianpeng zhang presented a regional power balance routing technique, which depends on smart chaotic ant colony. He also proposed a neighbor election plan to enhance the ant search ability. However, it was quite computationally inefficient [17].

Manikandan and Chinnadurai used minimal primary finding approach to enhance the performance of WSN and solve the power consumption issue. Shannon fano and Tuker process was utilized to select the optimal solution of each SN. However, the code was not generated automatically forsure [18]. Amudha, et, al surveyed the taxonomy of clustering process in WSNs. Here, clustering, CH election, routing and security were addressed. Various optimization and ML learning were discussed [19].

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Sridhar and Guruprasad proposed an energy efficient CWO approach for information collection in WSN. It was mainly used to find universal minimum resolution and rapid convergence rate. It was accomplished with various constraints such as power consumption, DPD percentage, DPL percentage and delay. Still, it has slow convergence speed and low accuracy [20].

Singh, et al reviewed the nature-inspired minimization techniques regarding the optimal coverage in WSNs. Here, researcher used integration of GA and Binary ACO approach for optimization. However, this approach was difficult to implement, debug, and optimize [21]. Qien, et al presented a cluster-based power minimization technique in WSN with MS node. It effectively constructs the power density purpose of MS to improve the possibility of inaccessible SNs. The researcher had designed the adaptive adjustment function to enhance the adaptability of CH. Moreover, it stands to be relevant complexity [22].

Padmalaya, et al reviewed a routing in WSN by utilizing ML techniques. Few interesting operations like routing, localization and element chasing has been done. few routing problems has also been discussed to know the performance efficiency [23]. Behura and Manas proposed a minimization-based routing for WSN using machine learning. Here, hybridization of C-means donkey–smuggler minimization approach. This was designed to attain an entire routing performance in WSNs. Though it has high searching ability, it is too sensitive to elect the starting cluster number [24].

Tarunpreet and Dilip reviewed an QoS mechanism in WSN. It was performed for computational intelligence-based routing protocol. This survey shows the systematic review of entire QoS mechanisms and shows the performance issue in WSN [25].

Based on this survey, the overall workflow of this proposed methodology is explained in upcoming section.

III. PROPOSED APPROACH

3.1 Energy Consumption Model

Typically, a communication unit posses a transceiver. At first, the transmitter consists of sensor nodes, which uses a huge amount of energy to the construct radio microchip technology and amplifier circuit. Next, the receiver uses energy at the time of receiving information that depends on the interactive distance. If the interactive items are detached by distance (dis) and it is minimal than the threshold distance, then the empty space power utilization device is engaged to evaluate the energy or else, multi-path mechanism is applied.

In addition, the feature for data aggregation is encapsulated for cluster head to base station. Energy required to transmit n-bit of data at distance *dis* is evaluated by using equation 3.1. Here, Ey_{elec} is denoted as energy, which is used for transmitting and receiving digital circuit. It is utilized for transmitting single bit information. Ey_{tx} and Ey_{rx} represents the energy used by both transmitting and receiving unit. It is mainly used to transmit L sized packet information.

This transmission is performed based on two techniques namely, digital coding and digital modulation. Ey_{fsm} and Ey_{mpm} that indicates amplifier cost of transmitter for free space mechanism and multi-path model. Moreover, power setting is controlled by power amplifier. This controlling process is held only when the communication distance dis between transmitter and receiver is lesser than dis_0. In this stage, the free space energy loss technique is used for power estimation.

When energy needed on data transmission in empty space approach is estimated as follows,

$$Ey_{tx}(L, dis) = LEy_{elec} + LEy_{fsm}dis^2 dis << dis_0 \tag{3.1}$$

If the distance dis is higher than the threshold measure, then the multipath technique is selected to evaluate energy by using the following equation,

$$Ey_{tx}(L, dis) = LEy_{elec} + LEy_{mpm}dis^4 dis >> dis_0 \tag{3.2}$$

Energy utilization at the receiver end is denoted as follows,

$$Ey_{rx}(L, dis) = Ley_{elec} \tag{3.3}$$

Here, *L* indicates the data packet length in communication bit count. And also dis_0 value is evaluated as follows,

$$dis_0 = Sqrt\,(Ey_{fsm}) / Sqrt\,(Ey_{mpm}) \tag{3.4}$$

This proposed methodology operates in two stages. First one is clustering that is performed by using the Integration of Novel Memetic and Brain Storm Optimization approach with Levy Distribution (IoNM-BSOLyD) using the fitness function. And the second one is routing. Here, routing is performed by using Water Wave Optimization with Hill Climbing (WWO-HCg) technique. Entire operation performed by this proposed methodology is completely explained in the upcoming sections.

3.2 Cluster Formation

The SNs in the network are clustered together by using IoNM-BSOLyD approach. Here, the Novel Memetic (NM) algorithm is effectively integrated with the Brain Storm Optimization with Levy Distribution (BSOLyD) to enhance the performance of this proposed methodology.

3.2.1 NM Algorithm

In this section, complete workflow of this proposed Novel Memetic (NM) approach is presented. Initially, the derivation of the fitness function is explained. After that, the election of Cluster Head (CH) and the load balanced cluster formation approach are designed. Here, the CH is elected based on the SN

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degree, intra-cluster communication distance and remaining energy of SN in network.

Fitness Criteria:

To estimate fitness value, we need to consider some following metrics.

a. Node Degree

The Sensor Node (SN), which has huge amount of Cluster Member (CM) is elected as CH. Node degree is estimated as follows,

$$Minimize\ f_{N\text{-}D} = 1/\ sum\ (cm_a) \quad (3.5)$$

where, N-D represents the node degree, a varies from 1 to s, cm_i indicates the CM of a^{th} cluster, and s denotes the total number of CHs.

b. Intra-Cluster Communication Distance

The SN votes the node, which has Minimum average distance between the CM and CH which is elected as CH. Therefore, the execution cost of this intra-cluster communication is always low. It is estimated as follows,

$$Minimize\ f_{I\text{-}CC} = 1/s\ dis\ (CH_b,\ Cm_a)/(CM_b) \quad (3.6)$$

Here, a varies between 1 to Cm_a, $dis\ (CH_b, Cm_a)$ denotes the distance between b^{th} CH and a^{th} CM.

c. Remaining Energy

To elect CH, the remaining energy plays a vital role. Part of CH is to collect the data from CM. Some of the CH acts as a relay node. It is mainly used to send the information towards sink node. The SN is elected as CH, when the residual energy of that SN is high.

$$Minimize\ f_{RE} = s/\Sigma^{s}_{a=1}\ Ey_{resdl} \quad (3.7)$$

where, s indicates the number CH in network and Ey_{resdl} denotes the residual energy of s^{th} CH. Node degree, intra-cluster communication distance, and residual energy parameters are used for the election of CH. Fitness function is estimated by associating these three parameters by utilizing weighted sum technique, which is indicated as follows,

$$Ftfn = wt_1 * f_{N\text{-}D}+wt_2 *f_{I\text{-}CC}+wt_3*f_{RE} \quad (3.8)$$

Here, wt1, wt2, and wt3 represents the weight factors, and its value ranges between 0 to 1. The enhancement of this algorithm holds multiple key factors such as representation, initialization, fitness/objective function estimation, election technique, mutation, and crossover. This NM algorithm is clearly stated below,

Pseudocode for NM Algorithm

Step 1 *: MEMI clustering ()*
Step 2 *: Induce initial population pop // various modification of SN identity*
Step 3 *: Amend population by local search.*
Step 4 *: Extract cluster headset from each modification.*
Step 5 *: Evaluate the fitness function using* ***equation.***
Step 6 *: while (end principle is not met)*
Selection Phase
Step 7 *: Elect the chromosome for recreation.*
Crossover and Mutation Phase
Step 8 *: Exploit crossover and mutation*
Step 9 *: Done solution minimization by local search*
Step 10 *: Estimate the fitness value*
Step 11 *: end while*
Step 12 *: while (no best solution was found)*
Step 13 *: Repeat step 4*
Step 14 *: End procedure MEMI clustering*

This MEMI algorithm is embedded with Brian Storm Optimization algorithm to provide better cluster formation. It is clearly explained below.

3.2.2 BSOLyD Approach

The process of BSO approach depends on brain storm model. It is an easy and adequate swarm intelligence technique, which effectively characterizes the execution of clustering and the population variation. This approach plays multiple roles during the implementation for various practical issues.

Moreover, BSO uses K-means algorithm to choose local optimum during clustering. At the time of population variation, this BSO algorithm generates novel individuals through the mutation approach based on the local optimum value. Therefore, it clearly states that the clustering and variation plays major role in this BSO technique to ensure the diversity of model and also the accuracy.

At first, initialize the population, later, use the clustering method through which individuals for k clusters are obtained. Local optimum value of each cluster is represented by cluster center. Data is optimized via learning to promote local search during updating and variation process. It effectively improves the group diversity and deduces the degree of coupling between classes.

The deduction is done via fusion mutation operation performed by individuals and inter-class individuals to boost up the global search. Basic algorithm for BSO is shown in Algorithm 1.

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Step by Step Procedure of BSO Approach

Step 1 *: Initialize population by provoking p individuals randomly.*

Step 2 *: Adaptive measure of individual is estimated.*

Step 3 *: Using clustering process, the p individuals are clustered into s clusters.*

Step 4 *: By comparing adaptive values of individuals in cluster, better individual in cluster is selected as cluster center.*

Step 5 *: Induce number between 0 to 1 in a random manner.*
(i) if the number is lower than the pretend probability constant p_{5g},
(a) Cluster center is elected in a random manner
(b) individual is induced in a random manner to change the cluster center.
(ii) else, do nothing

Step 6 *: New individual is induced and originate the number between 0 to 1 in a random manner.*
(i) If the number is lower than the pretend probability parameter p_{6a},
(a) Elect cluster in arbitrary manner.
(b) Induce measure between 0 to 1.
(c) If the measure is lower than the pretend probability constant p_{6iaaa}, *elect cluster center, update random values to induce new individuals.*
(d) else, elect ordinary from class, and update random measure to induce new individual.
(ii) Else, elect dual cluster to induce new individual.
(a) Induce number between 0 to 1 in arbitrary manner.
(b) If the number is lower than the pretend probability constant p_{6iiaa}, *associate the cluster centers of dual clusters, and update random measure to induce new individuals.*
(c) else, associate same individuals of dual clusters and update random number to induce new individuals.
(iii) Flexible value of currently induced individuals is distinguished with similar subscript past individual, and individual with better fitness measure is the novel individual of upcoming process.

Step 7 *: If n individuals have been induced, then reach step 8, else go back to step 6.*

Step 8 *: If the pretend highest number of the processes is attained, end, else go back to step 2.*

This NBSOA algorithm is integrated with Levy Distribution model for clustering. In this model, four vital functions are enclosed . Entire factors which is required for effective clustering. It effectively saves the energy by restraining the CH count. It also identifies the current energy ratio and deduces the distance between CH and Base Station (BS). Moreover, alleviation of intra-cluster distances, and enhances inter-cluster distance from CH.

Load balancing between CHs is done. When SN are originated after deployment, then the fitness function is derived by using three different constraints to elect the minimal group of CHs in WSN. Basically, NBSO approach is an extension of swarm based meta-heuristic technique. It is operated based on the human brainstorming metabolism. It mainly used to resolve the issues in associated and distributed diverse plans.

In general, this principle consists of three vital phases, such as, clustering, novel individual creation, and election. At first, clustering appetites to gather unique solutions as condensed portions. So that, replication of same individuals is limited. In addition, based on some constraints, the new individual has been deployed.

At first, unique solution is ingrained depending on multiple individuals, which are recommended by traditional BSO. It effectively describes the probability $Pbty_{gentn}$, which is applied to estimating that the novel solution is induced by enormous individuals. It enhances the examination when the novel individual is induced from cluster and enhance the resident results.

Bearing result of dual clusters are located aside from clusters. Nevertheless, it is advisable for exploration. This approach defines dual specific constraints such as $pbty_{1cluster}$ and $pbty_{2cluster}$, which demonstrates the chance for enhancing the solution.

Let us consider that p belongs to R^n as a flexible solution. There is problem with n number of features. Once the clustering is completed, based on some constraints, the BSO provides an individual for reasonable solution. It is integrated with the replica of minimal result or the association of different results from dual clusters. It is governed by $pbty_{gen}$, $pbty_{1cluster}$, and $pbty_{2cluster}$ possibilities.

On the other hand, induce new individuals and consider it as a convex integration of two remaining one. By satisfying the following constraints, the new individuals are redistributed.

$$p^a{}_p = p^b{}_z + c_1\,\varphi\,(tm) \tag{3.9}$$

where, $p^a{}_p$ indicates a^{th} decision constant of solution, p_a, $c_1 \sim L(0,1)$. tm represents the number of iterations. In addition, the value of φ is estimated as follows,

$$\varphi\ ™ = c_2\sigma(0.5tm\text{-}f)/r \tag{3.10}$$

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Here, $c2 \sim L(0,1)$, which effectively defines the randomly projected value. This value varies between 0 to 1. It is obtained by employing even supply. σ denotes the logistic sigmoid function, and tm indicates the entire iteration total. Atlast, impermanent individual a is estimated. Here, the optimization issue is deliberated, and lowest value of $f(a_a)$ is also pretended.

In this stage, if the novel individual is higher than the current individual, the last one is shuffled by novel individual automatically. Levy Distribution (LD) is embedded into this proposed methodology to ignore the BSO approach from local minimal issue. This LD originates a sudden drift in mathematical manner. Here, the Levy flight is an arbitrary gain method.

Therefore, the period duration of surfing process becomes improved with the sudden drift. It is illustrated as follows,

$$Levy\ (\alpha) \sim tm^{(-1-\alpha)}, \text{ where } 0<\alpha<2 \qquad (3.11)$$

where, tm indicates the arbitrary parameter, which ranges between 0 to 1, and α represents the stability index. The layout of the surfing region is represented as follows,

$$Levy\ (\beta) = k*\partial / |g|^{1/\beta} \qquad (3.12)$$

Here, k and g show the measure of normal distribution, and β denotes the Levy interpreter. once the starting process of population is completed in proposed IoNM-BSOLyD methodology, the frivolous individual is induced by some specific constraints. If c1( ) and c2( ) represents the arbitrary parameters then the frivolous individual should be,

$$A_x = A_{lyb} + i*Levy\ (\alpha) * (A_y - A_z) \qquad (3.13)$$

If not, the frivolous individual should be,

$$A_x = A_{ub} + i*Levy\ (\alpha) * (A_y - A_z) \qquad (3.14)$$

where, $c(\ )$ denotes the frivolous parameter. The Levy sanctioned solution commits to an unchanged feature of current individual when the proposed BSOA approach has not used the surf area in a proper manner. Once the clustering process is completed, the process steps into the routing process automatically, it is clearly explained below.

3.3 WWO-HCg BASED ROUTING

To resolve minimization issue in WSN, Water Wave Optimization (WWO) algorithm is used. It operates based on the shallow water wave models. The height of the wave gets enhanced when the wave excursion occurs from underground water to flat water, and vice versa. In this approach, the solution area A is comparable to the ocean bottom region. The depth of this ocean bottom region is inversely proportional to the fitness point.

During problem solving method, we consider three major operations on the waves, namely, propagation, refraction and breaking.

i. Propagation

Due to spin, ocean bottom agitation, inertial resistance and the operator reflects the energy dispersion. Let us assume that the wave ai of dimension b. Upgrading wave ai is generated by propagation operator, which is illustrated below,

$$a_{id} = a^d{}_i + c\lambda Lg^{dim} \qquad (3.15)$$

where, λ represents the upgraded value for entire processes. c indicates random value ranges between -1 to 1. Lg^{dim} is a length of dim*th* dimension ($1 \leq dim \leq b$). If it located outside of possible region, then a new position of A_x is randomly rearranged between surf regions. After the completion of propagation, the fitness value of both new and past wave is correlated.

The waves with highest fitness value is switched in a population. In addition, the height of the wave is rearranged as ht_{maxm}. Preferably, height (ht) of a_x is deduced by 1 and a_x. It is stable in which the power dispersion of mimics is considered as cortex shedding, bottom friction, and inertial resistance. Wavelength updates of entire processes are evaluated as follows,

$$\lambda_x(tm+1) = \lambda_x(tm)\ \alpha\ \exp\ (P/Q) \qquad (3.16)$$

where, $P = f\,(a_x(c)) - f_{minm} + \varepsilon)$ and also $Q = f_{maxm} - f_{minm} + \varepsilon$. tm indicates the value of current iteration. f_{maxm} and f_{minm} denotes the objective functions of both superior and inferior, respectively. α is a constant of wavelength deduction, and ε represents the small positive measure with ignore 0 in denominator of exponential term. This equation shows that the small wavelengths could hold highest fitness waves, which is applicable to proliferate within limited ranges.

ii. Refraction

If the wave ray is intermittent to bottom evaluation, then the wave direction is altered. It is proved that the wave rays mostly meet in flat region and deviate in deep region. If the overall height of the waves is zero, then the refraction operates in these waves. One-fourth of easy approach for estimating the location after refraction is stated below,

$$\partial_{xdim} = B\ (U/2\ ,\ V/2) \qquad (3.17)$$

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Where, $U = a^{dim}_{besf} + a^{dim}_i$, and also the $V = | a^{dim}_{besf} - a^{dim}_i|$. Here, B represents the usual distribution with standard deviation and average value, and a_{besf} is a minimal solution. dim^{th} dimension of i^{th} wave denotes the arbitrary measures between current dimensions. After the completion of iteration, height of the wave is boot to h_{maxm}. The wavelength is evaluated by using following equation,

$$\lambda_i\ (tm+1) = \lambda_a (f)\ (f(a_i) / f(a'_i)) \quad (3.18)$$

iii. Breaking

In this approach, the breaking process is applied on wave a_x, where x = 1,2,...N. It has a capacity to attain a new on a_{best}, but it is attained by determining *m* dimensions in a random manner. The value of m varies between *1* to m_{maxm}. The upcoming notation is mainly used to determine the single wave x'_a for dimension (*dim*) that is stated below,

$$x'_{id} = a^{dim}_x + N(0,1)\ \beta\ Ly^{dim} \quad (3.19)$$

Here, β denotes the variable for breaking. a_{best} indicates a single wave case, and it is not an appropriate wave. In general, the highest appropriate wave is developed in a small area by using propagation operator, and the lowest appropriate wave is developed in expanded areas.

Surf recession in the wave is ignored by the guidance of refraction operator. Due to this ignorance, the surf variegation and alleviate incomplete convergence gets enhanced. Numerous explorations are done by enabling the breaking operator in ambitious areas. Due to this exploration, the management is exhibited by primary wave operators between exploration and exploitation surf.

In this stage, to enhance the resident surfing capacity, the Hill Climbing (HC) effect is integrated with this proposed WWO algorithm. This HC is the simplest form of resident surfing method. Initially, it is started with an arbitrary result later it shifts from parent-to-child solution in an iterative manner.

As there is no minimal child solutions recognized some basic opinion of HC approach is ued, the resident surfing capacity of proposed WWO-HCg technique is enhanced.

IV. Results And Discussion

This proposed methodology deals with the ternary QoS aspect such as network delay, energy consumption, packet delivery ratio, network lifetime, and residual energy. In this section, comparison is made between the proposed IoNM-BSOLyD methodology with some existing approaches such as Fuzzy-based Unequal Clustering and Hybrid data transmission with ACO - based Routing (FUCHAR), Grey Wolf Optimization (GWO), and Multi-Objective Particle Swarm Optimization (MO-PSO). The performance analysis of this proposed research work is explained as follows,

4.1 Network Delay

Network delay is a major QoS parameter for forwarding information in a particular time constraint in a WSN environment. Time taken to position the data packets in the transmission link is named as transmission delay.

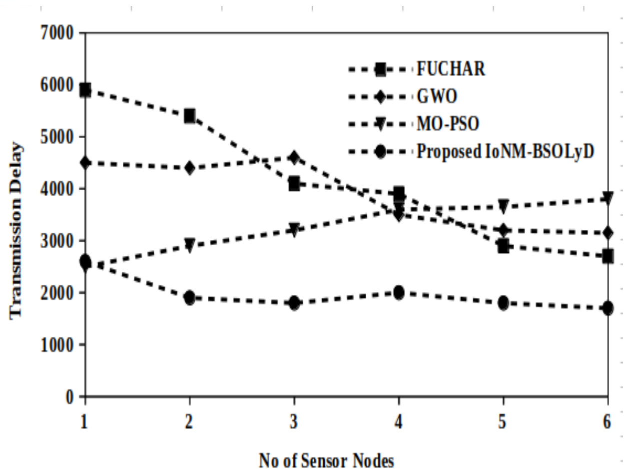

Figure 4.1 Comparative Analysis of Transmission Delay

This transmission delay is mathematically evaluated as follows,

$$TD\ \alpha\ L / S\ (dp) \quad (4.1)$$
$$TD\ \alpha\ 1 / BW \quad (4.2)$$

Where, *TD* indicates the transmission delay, *L* is a length, *S (dp)* represents the size of data packets, and *BW* is a bandwidth.

Figure 4.1 illustrates the comparative analysis between proposed IoNM-BSOLyD with existing FUCHAR, GWO, and MO-PSO techniques. It clearly shows that during data transmission, the delay occurred in this proposed methodology is comparatively lower than the existing approaches.

4.2 Energy Consumption

The proportion between the starting energy and SN lifetime in WSN is named as energy consumption. It is estimated as follows,

$$E_{cpn} = \frac{E_0}{b_a} \quad (4.3)$$

where, E_{cpn} indicates the power consumption, E_0 is the opening energy, and b_a represents the SN lifetime in WSN.

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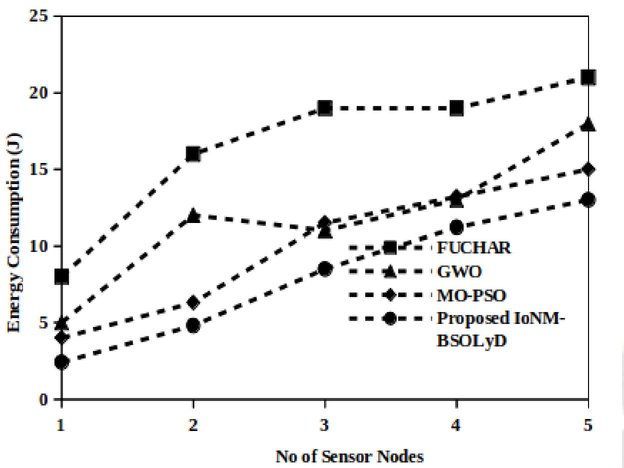

Figure 4.2 Comparative Analysis of Energy Consumption

Figure 4.2 shows the execution investigation of energy consumption. It is estimated in Joules (J). Here, the energy consumed by the proposed IoNM-BSOLyD approach is lower than the existing FUCHAR, GWO, and MO-PSO techniques. Therefore, each SN in the network holds long time during processing, so there is an automatic increase of QoS network rapidly.

4.3 Packet Delivery Ratio

PDR is the amount of data packets acknowledged at the end point to the amount of data packets sent form the source node. It is estimated as follows,

$$PDR = N(dp_{des}) / N(dp_{sou}) \quad (4.4)$$

where, $N(dp_{des})$ represents the amount of data packets at end point and $N(dp_{sou})$ denotes the amount of data packets sent from source node.

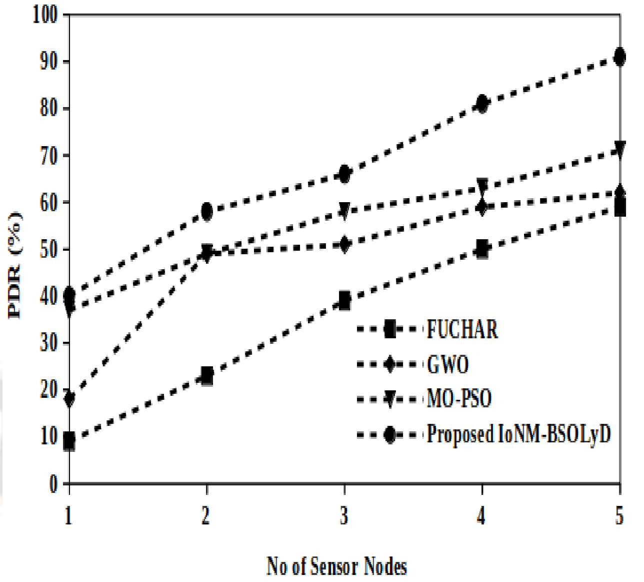

Figure 4.3 Comparative Analysis of PDR

Figure 4.3 demonstrates the DR of the data packets in terms of percentage. The PDR of the presented IoNM-BSOLyD approach is related with the existing FUCHAR, GWO, and MO-PSO techniques. Here, PDR of the proposed IoNM-BSOLyD methodology is relatively higher than the existing one. When the PDR gets increased, then the highest amount of data packets is transmitted without any delay automatically. Because transmission delay is comparitively less in this proposed methodology.

4.4 Network Lifetime

Energy of SN in network runs out to transmit data packet at particular time period of time is named as network lifetime. It is estimated as follows,

$$NwLt = min_b \left[\frac{\sum_{p=1}^{l} s_{ab} * b_a}{k_b}\right] \quad (4.5)$$

where, $NwLt$ is the network lifetime, s_{ab} denotes the coverage matrix, b_a represents lifetime of SN, and $k_b = k$, and $l=1,2,\ldots,n$.

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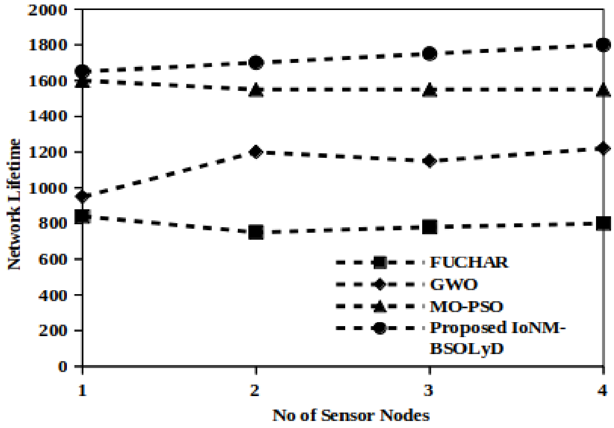

Figure 4.4 Comparative Analysis of Network Lifetime

Figure 4.4 illustrates the comparative study of network lifetime. The comparison is made between the proposed IoNM-BSOLyD approach with the existing FUCHAR, GWO, and MO-PSO techniques. This is the major QoS parameter in WSN, which takes a major role to enhance the overall performance of the system.

4.5 Residual Energy

It is a deflection among the starting power and utilized power of SN in WSN that is evaluated as follows,

$$E_{resdl\_engy}=E_{st\text{-}engy}\text{-}E_{utd\text{-}engy} \quad (4.6)$$

where, E_{resdl_engy} is the residual energy of SN, $E_{st\text{-}engy}$ represents the initial energy of SN, and $E_{utd\text{-}eny}$ is the consumed power of SN in network.

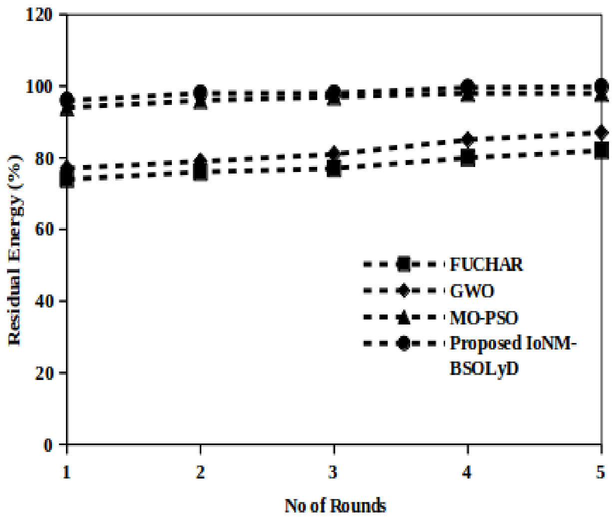

Figure 4.5 Comparative Analysis of Residual Energy

One of the major QoS parameter in WSN is residual energy. Because, when the residual energy of SN becomes low, then the life of SN is enhanced automatically. Therefore, it consumes lesser amount of energy for data packet transmission. Figure 4.5 clearly illiustrates the comparative analysis of both proposed and existing approaches. Here, by using the proposed IoNM-BSOLyD approach, the SN in the network uses lesser energy than the existing FUCHAR, GWO, and MO-PSO techniques.

V. CONCLUSION

This research work has effectively designed the IoNM-BSOLyD approach using the fitness function for clustering and WWO-HCg for routing. Here, the SNs in the network are clustered by using IoNM-BSOLyD approach. In this approach, CH is elected based on the node degree, intra-cluster communication distance, and residual energy of SN in the network. This CH holds the entire information of the cluster member in the cluster. Therefore, the information related to cluster member is obtained from CH and transmited to BS via internet. After that the clustering of SN in WSN gets completed, routing is performed by using WWO-HCg technique to elect an optimal route among the source and the destination nodes in WSN. This proposed methodology deals with various QoS aspect such as network delay, energy consumption, packet delivery ratio, network lifetime and security. By selecting the optimal path during routing, this proposed methodology enhances the performance of QoS metrics as well. This proposed IoNM-BSOLyD approach protocol provides better performance results than when compared to contemporary protocols such as existing FUCHAR, GWO, and MO-PSO techniques.

In future, in order to power up the SN in WSN, energy harvesting technique will be used to achieve the target of operational network.

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