Energy-Aware Ch Selection And Optimized Routing Algorithm In Wireless Sensor Networks Using Wmba And Qoga

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Abstract: WSN is widely used in different applications, such as smart grid, water municipals, and health care, for monitoring the health condition of a patient, etc. But, the major challenge of WSN is energy efficiency. Energy Efficient-based WSN has always been a research focus to improve its performance. Aiming at optimal energy utilization to improve life expectancy with guaranteed QoS, an optimal CH selection and optimal routing algorithm in WSN is proposed. The work has carried out the selection of the CH based on various factors, such as residual energy of the nodes, proximity, distance to the base station, cost, node degree, and node centrality or coverage, using the proposed WMBA. After that, an optimal path selection using QOGA is done between CH and BS based on various factors, such as distance, residual energy, and node degree, under the MKMA clustering process. The experiment shows that the proposed methodology achieves better life expectancy for the WSN by achieving an energy consumption of 975J for the entire round of 2000 and a PDR of 93.56%, and remains to be energy efficient compared to the existing state-of-art methods.

Keywords: wireless sensor network (WSN), quality of service (QoS), cluster head (CH), wavelet mutation bat algorithm (WMBA), quasi opposition based grasshopper (QOGA), modified k-means clustering (MKMA), packet delivery ratio (PDR)

1. Introduction

Wireless Sensor Network plays a vital role in many commercialized industrial automation processes and various other real-life applications [1]. WSN is a network of small, self-sufficient gadgets called sensors [2]. Sensors are nothing but tiny electrical devices, which comprise sensing mechanisms to collect data from Physical or Environmental Conditions (e.g., temperature, sound, vibration at various areas), process the information, and transmit the detected data to the base station [3,4]. It is a known fact that WSN is a resource-constrained network in which energy efficiency is always the main issue since the operation of WSN depends heavily on the life span of the sensor node's battery [5,6]. The most energy-consuming operation in WSN is the data packet routing activity. Routing strategies are required for transferring data between sensor nodes and the base station [7].

Routing in WSN is different than traditional IP network routing because it exhibits many unique characteristics, such as it is unrealistic to build a global addressing scheme for a large number of sensor nodes [8]; secondly, all utilization of sensor systems require the stream of detected information from numerous sources to a specific BS [9]. These unique characteristics are often taken into account for addressing the issues and challenges related to network coverage, runtime topologies management, node distribution, node administration, node mobility energy consumption, network deployment, and so forth. Thus, such limitations should be avoided, and efficiency should be ensured [10].

The Routing algorithms are classified into two categories. They are direct routing and indirect routing. In direct routing algorithms, each node in the WSN directly forwards the gathered data to the sink node. Contrarily, indirect routing algorithms are like those clustering algorithms. In detail, Clustering Protocols in which the area is divided into clusters and Cluster heads are assigned to each cluster [11]. All the nodes in the cluster send data to corresponding cluster heads, and then the cluster head sends it to the Base station. Clustering is suggested to WSN due to its advantages, such as energy-saving, network scalability, and network topology stability [12]. It also decreases the overheads due to communication, thereby reducing interferences and energy consumption among network nodes. Besides, clustering improves the efficiency of data relaying by decreasing the number of nodes required to forward data in the WSN using data aggregation at CH by intra-cluster communication decreases overall packet losses. However, clustering algorithms have some disadvantages, such as additional overheads during CH selection, cluster formation, and assignment process [13, 14].

To conquer such challenges, various methodologies, such as Hierarchical Data Dissemination Strategy (HDDS)[15], Low-Energy Adaptive Clustering Hierarchy (LEACH)[16], Particle Swarm Optimization[17], Spatial and energy-aware trusted dynamic distance source routing algorithm (SEAT-DSR)[18] are developed in which hot-spot issue is a significant concern around sink nodes where large amounts of data are merged. In fact, as the hop distance to a sink decreases, the traffic on CH quickly intensifies. Hence, there is a relationship between the hop-distance to a sink node and the amount of data that has to be forwarded. This uneven energy consumption of the CH node can rapidly disconnect the entire WSN if the communications are extended. Many proposals have concentrated on this problem. However, they have their performance limitation [19, 20]. Hence, the work proposed an Energy-Aware CH Selection and Optimized Routing Algorithm in WSN Using WMBA and QOGA algorithms.

The draft structure of this paper is systematized as Section 2 surveys the associated works regarding the proposed method. A brief elucidation of the proposed work is proffered in section 3. Section 4 explores the experimental outcome, and section 5 concludes the proposed work with future scope.

2. Literature Survey

Farman Ullah *et al.*[21]developed an Energy-Efficient and Reliable Routing Scheme (ERRS) for resource-constrained Wireless Body Area Network (WBAN). The scheme had the advantage of adaptive static clustering routing technique, enhanced stability period, longer network lifetime, and maximized reliability. Experimentation results showed that the scheme was improved by 17% and 40% than SIMPLE and M-ATTEMPT, respectively. But it had a limitation of slow response time due to the longer distances of some nodes from the sink.

Denghui Wang *et al.* [22] recommended an Energy-Efficient Distributed Adaptive Cooperative Routing (EDACR) for Wireless Multimedia Sensor Networks WMSN, which used the constraints of QoS and also ensured that the energy was distributed more efficiently at the same time. The results showed that the energy consumption was reduced when compared with the existing protocols. But it had a limitation of data redundancy.

Premkumar Chithaluru *et al.* [23] developed an Adaptive Ranking Based Energy-Efficient Opportunistic Routing Protocol (AREOR), which identified the most effective node that participated as a cluster head. Thus, the scheme played a vital role in the energy optimal forwarder node selection. The parameters, such as Message Success Rate, End-to-End delay, and Packet Delivery Ratio, demonstrated the scheme's effectiveness. The experimental result showed that the scheme had an incremental gain of 0.3%, but it had a limitation, such as energy consumption.

Pratyay Kuila *et al.*[24] developed Linear and Non-linear Programming, which was formulated for two fundamental optimization problems in wireless sensor networks, i.e., energy-efficient routing and clustering, respectively, based on particle swarm optimization. Thus, the energy consumption of the scheme was significantly balanced, and the lifetime of the network was improved. The experimental results showed that the scheme performed better network life, the number of inactive sensor nodes, and the total data packet transmission. But it had a limitation of transmission delay and communication overhead.

Riham Elhabyan *et al.*[25]developed a centralized multi-objective Pareto optimization approach, which found a joint solution for both the clustering and routing problems in WSN. The scheme was energy efficient, reliable, and scalable. The experimental result showed that the scheme outperformed the average consumed energy per node, number of clustered nodes, the throughput at the BS, and execution time. But it had an issue of prolonged overall network lifetime.

Khalid A. Darabkh *et al.*[26] developed an Energy-Aware and Layering-Based Clustering and Routing Protocol (EA-CRP) that gathered data in WSN. The scheme shortened the communication distance between nodes and decreased the amount of intra-cluster communication overhead. The experimental result showed that the scheme had superior performance in terms of network lifetime, energy efficiency, and scalability. But it had a limitation of runtime topology management.

Deepak Mehta *et al.*[27] developed a Multi-Objective Based Clustering and Sailfish Optimizer (SFO) guided routing method and sustained energy efficiency in WSN. The scheme was used for optimal path selection during data transmission to the base station. The simulation results showed that the scheme had performed 21.9% and 24.4% better in terms of energy consumption and the number of alive sensor nodes respectively. But it had suffered from the cost of long-range transmissions.

3. Proposed Energy Aware Optimal Ch Selection And Optimal Path Routing

In WSN, sensor nodes are characterized to have a short life span due to continuous sensing, and consequently, the battery drains quickly. At the time of heavy traffic conditions, sensors close to the sink die quickly and initiate an energy-hole problem. Thus, optimal usage of available energy is a key challenge in WSN assisted applications. A precise clustering creates clusters and assigns specific tasks to cluster heads, provides an optimal routing, and majorly contributes towards scalability, lifetime, and overall energy efficiency of the system. The work has developed an Energy-aware CH selection, and Optimized Routing Algorithm in Wireless Sensor Networks using WMBA and QOGA as shown in Figure 1.

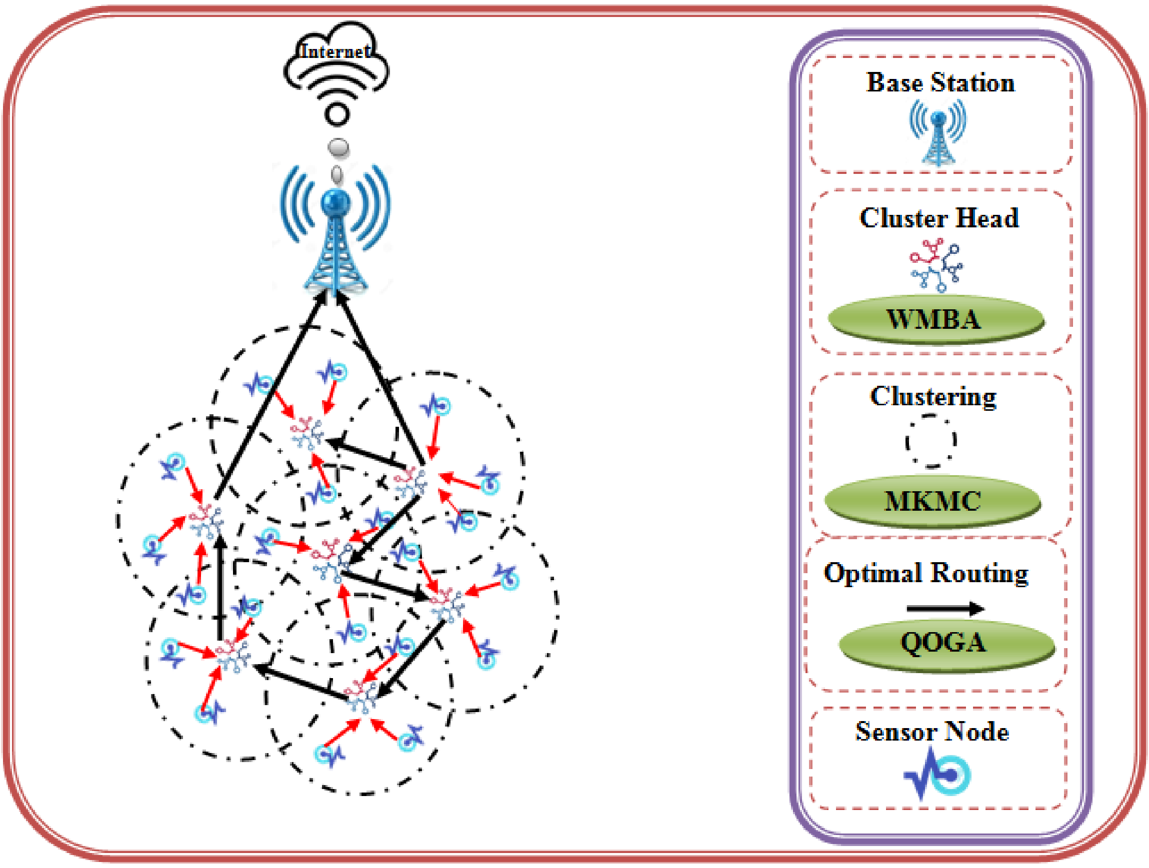

Figure 1: Proposed architecture for optimal CH selection and path routing for energy-aware

3.1. CH Selection

Cluster head groups the sensors into clusters to decrease the network energy consumption and increase the scalability of the network. Thus, the selection of CH is most important as there may be a chance of bottleneck and unbalanced energy consumption of the CH node, which can quickly disable the entire network if the communications are prolonged. In order to conquer the existing issues, the work has initiated a selection of CH using a wavelet mutation-based bat algorithm (WMBA). The CH selections are carried out by three essential characteristics of the bat algorithm: echolocation, frequency, and loudness. The selection is made based on various features, such as residual energy of the nodes ($\aleph_{res}$), proximity ($\aleph_{prox}$), distance to the base station ($\aleph_{db}$), cost ($\aleph_{\cos t}$), and node centrality or coverage ($\aleph_{\text{cov}}$). The objective of selecting the cluster head is given by taking a weighted sum approach (Γ_i) for different features and forming into one scalar objective function given as:

$$\Re_{fitness} = \Gamma_1 \times \aleph_{prox} + \Gamma_2 \times \aleph_{\cos t} + \Gamma_3 \times \aleph_{res} + \Gamma_4 \times \aleph_{\text{cov}} + \Gamma_5 \times \aleph_{db} \tag{1}$$

i.e,

$$\Re_{fitness} = \Gamma_1 \times \frac{1}{C_T}\sum_{i=1}^{N} P_{prox}(C_i) + \Gamma_2 \times \frac{1}{C_T}\sum_{i=1}^{N} C_{\cos t}(C_i) + \Gamma_3 \times \sum_{i=1}^{N}\frac{1}{C_T} + \Gamma_4 \times \frac{1}{C_T}\sum_{i=1}^{N}\frac{\sqrt{D_{db}(s_i, C_i)}}{network dimension} + \Gamma_5 \times \frac{1}{C_T}\sum_{i=1}^{N} D_{db}(s_i, C_i) \tag{2}$$

Where, $\Gamma_1 + \Gamma_2 + \Gamma_3 + \Gamma_4 + \Gamma_5 = 1$ and the goal of the WMBA is to maximize the value of the fitness as given below:

$$\chi_{objective} : Maximize \Re_{fitness} \tag{3}$$

The maximization of the objective function is carried out by adjusting the parameters of WMBA, such as frequencies, loudness, and pulse emission rates of the bat.

Initially, the position and velocity of the bat in an n-dimensional search space is given as follows:

$$\gamma_f = \gamma_{\min} + (\gamma_{\max} - \gamma_{\min}) \times \varphi \tag{4}$$

$$\nu_i^t = \nu_i^t + (\chi_i^{t-1} - \chi_{best}) \times \gamma_f \tag{5}$$

$$\chi_i^t = \chi_i^{t-1} + \nu_i^t \tag{6}$$

Where, γ_f denotes the frequency for adjusting velocity change, $\gamma_{\min}$ and $\gamma_{\max}$ represents the minimum and maximum pulse emitted by the bat, φ is a generated vector randomly based on

the distributed Gaussian, ν_i^t and χ_i^{t-1} illustrates the bat location and velocity in n-dimensional search space and χ_{best} is the global best solution. Now, new bats location is generated by exploiting phase strategy as given below:

$$\chi_i = \chi_i + \forall \times \mathrm{A}_i^t \tag{7}$$

Where, $\forall$ represents a wavelet mutation-based updation of the bat new location, and it is given below:

$$\forall_i^t = \begin{cases} \chi_i + \sigma \times (\chi_{i,\max} - \chi_i), & if \sigma > 0 \\ \chi_i + \sigma \times (\chi_{i,\max} - \chi_{\min}), & f\sigma \le 0 \end{cases} where\, \sigma = \frac{1}{\sqrt{a}} e^{-\frac{x^2}{2}} \cos(5)\left(\frac{x}{a}\right) \tag{7}$$

Where, the i^{th} element ranges between $[\chi_{\min}, \chi_{i,\max}]$ at the t^{th} iteration as mutated above. Now, the loudness of the bat is computed as:

$$\mathrm{A}_i^{t+1} = \alpha \times \mathrm{A}_i^t \tag{8}$$

Where, α is a variable constant. The symbol represents the pulse emission rate λ which is calculated as:

$$\lambda_i^{t+1} = \lambda_i^0 \times \left[1 - e^{-\varsigma \times t}\right] \tag{9}$$

Where, ξ is the constant variable. In the process, this rate λ is considered as the control to switch the global and local search. If a random number is greater than λ, a local search with a random walk is triggered. Thus, by altering the frequency, loudness, and pulse emission rate, the best fitness for maximizing the objective is obtained. Thus, the overall outline of the proposed WMBA is illustrated in figure 2 in the form of pseudo-code.

Input: Objective Function $\Re_{fitness} = \Gamma_1 \times \aleph_{prox} + \Gamma_2 \times \aleph_{cost} + \Gamma_3 \times \aleph_{res} + \Gamma_4 \times \aleph_{cov} + \Gamma_5 \times \aleph_{db}$
Output: CH selection

Begin
    Initialize the frequency (γ_f), loudness (A_i^t), and pulse emission rate (λ_t)
    While $(stopping\ criteria\ not\ satisfied)$ **do**
        Generate new solution by updating the frequency using,
            $\gamma_f = \gamma_{min} + (\gamma_{max} - \gamma_{min}) \times \varphi$
        Update velocity and position of the Bat using,
            $v_i^t = v_i^t + (\chi_i^{t-1} - \chi_{best}) \times \gamma_f$
            $\chi_i^t = \chi_i^{t-1} + v_i^t$
        Update the new location of the bat using,
            $\chi_i = \chi_i + \forall \times A_i^t$
        If $(\chi_i > A_i)$ **then**
            Obtain a best solution by performing wavelet mutation using,
                If $(\sigma > 0)$
                    Generate a local solution using,
                        $\forall_i^t = \chi_i + \sigma \times (\chi_{i,max} - \chi_i)$
                Else
                    Generate a local solution using,
                        $\forall_i^t = \chi_i + \sigma \times (\chi_{i,max} - \chi_{min})$
                End if
        End if
        If $(\chi_i < \lambda_t)$ and $(\chi_i < \chi_{best})$
            $\chi_i = \chi_{new}$
        Else
            Increase A_i and reduce λ_t using,
                $A_i^{t+1} = \alpha \times A_i^t$
                $\lambda_i^{t+1} = \lambda_i^0 \times \left[1 - e^{-\varsigma \times t}\right]$
        End if
    End while
    Rank the bat for the best solution that is CH
    Find the best CH
End Begin

Figure 2: Pseudo Code for WMBA

3.2. Clustering

Clustering forms a cluster based on the distance to CH and the energy of CH. The proposed Modified K-Means clustering conquer the current issue that considers only the distance measures between the CH and Sensor nodes, which disturbs the network's lifetime.

The MKMC groups a similar sensor node to the CH and forms a cluster. This helps to save energy efficiently. Initially, the proposed algorithm chooses a random CH from the sensor nodes $S_N = \left[S_1^*, S_2^*, S_3^*, S_4^*, ...S_N^*\right]$:

$$\zeta_{CH} = \left[CH_1^*, CH_2^*, CH_3^*, CH_4^*, ...CH_N^*\right] \quad (9)$$

Thereafter, Euclidean distance is calculated between each sensor node (S_K^*) and randomly selected CH (CH_K^*), which provides to evaluate the distance between the nodes:

$$\hbar_{\kappa}^{D} = \sum_{k=1}^{k} \left| CH_{\kappa}^{*} - S_{K}^{*} \right|^{2} \tag{10}$$

Now, CH energy potential is calculated:

$$S_p = \frac{\omega \times energy(CH_k)}{\hbar_{\kappa}^{D}} \tag{11}$$

Where, S_p sensor node potential $\hbar_{\kappa}^{D}$ specifies the Distance among the cluster head and sensor; $energy(CH_k)$ represents the residual energy of the respective CH; the sensor is allocated to a particular CH which has higher potential. If the distance between the sensor nodes and two different CH is the same, then the sensor node that connects with the CH has higher energy.

Now, based on the above working flow, the various data is grouped into various clusters

$$S_C^{New}(CH_K) = \left[S_k^1(CH_1^*), S_k^2(CH_2^*), S_k^3(CH_3^*), S_k^4(CH_4^*) \ldots S_k^n(CH_N^*) \right] \tag{12}$$

Thus, MKMC Forms a cluster and selects the appropriate cluster head to bring maximum network lifetime, reduce the number of message exchanges, and get independent time complexity of network growth.

3.3. Routing

Routing provides a route to transfer the data from CH and the base station. The defined route should be optimal to consume energy. It is necessary to perform routing; so that with the least amount of energy, the data is routed to the base station. But in existing methodologies, there is an energy constraint that when any node wishes to send data to the base station, it encounters quick energy discharge and ultimately the loss of the entire network. In order to conquer the existing challenge, the work has developed a Quasi Opposition-based Grasshopper Algorithm (QOGA) that selects the optimal route based on the distance, residual energy, and node degree. The aggregated data of the CH are sent to the BS via the identified optimal path. The optimal path is identified by the QOGA based on the fitness function given by:

$$CH_{fitness}(\wp_i) = \Psi_1 \Phi_{RES} + \Psi_2 D_{CH,BS} + \Psi_3 \mathrm{N}_d \tag{13}$$

Where, Ψ_1 Ψ_2 Ψ_3 denotes the weighted values. The first priority for avoiding the sensor node with inadequate energy is residual energy (Φ_{RES}), because node failure during communication causes the sensor node with lower energy. In order to achieve the shortest way possible to minimize energy consumption, the distance between CH and BS ($D_{CH,BS}$) has been considered as a second priority. The third priority for choosing the next hop CH node, with fewer cluster members, is the Node degree (N_d).

QOGA provides an apt solution based on the location of each grasshopper for the optimization problem, as stated in the equation. Grasshopper location that is the fitness function, is signified by $\wp_i$ and represented by the following equation:

$$\wp_i = \eta_i + \mathrm{H}_i + \mathrm{I}_i \tag{14}$$

The motion of grasshoppers is observed based on the important three components mentioned below in the equation. Social interaction is the main component that has been developed by the grasshoppers themselves. It is mathematically expressed as:

$$\eta_i = \sum_{j=1, j \neq 1}^{N} \eta\left(\ell_{ij}\right) \ell_{ij} \tag{15}$$

Where, ℓ_{ij} denotes the separation among the grasshoppers i^{th} and j^{th} that is $\ell_{ij} = \frac{\upsilon_j - \upsilon_i}{\ell_{ij}}$, which denotes a unit vector directed from i^{th} grasshopper to the j^{th} grasshopper.

The strength (η) of the social forces is mathematically expressed as:

$$\eta(\kappa) = fe - \kappa / l - e - \kappa \tag{16}$$

Where, f denotes the attraction intensity and l illustrates the attractive length scale.

The observed Repulsive forces are within the range of (0, 2.079) for the separation interval of 0 to 15. The grasshoppers are said to be in their comfort zone when the repulsive force between two grasshoppers tends to be exactly 2.079 units which means that the offensive and attractive forces between the grasshoppers are in equilibrium. Their swarming capacity influences grasshoppers by their attractive forces, repulsive forces, and grasshopper trajectories. This means that two hoppers are divided into three regions: the attraction area, the comfort zone and the repulsion area. For the wide separations between the grasshoppers, strong forces are not applicable. Thus, the mapping and setting of the separation interval between the grasshoppers are fixed as (1, 4).

The H_i component mentioned in Equation (17) is determined as shown below:

$$\mathrm{H}_i = -a\hat{c}_G \tag{17}$$

Where, a = gravitational constant $\hat{c}_G$ = unity vector directed towards the centre of the globe. The I_i component mentioned in is determined, as shown below:

$$\mathrm{I}_i = \upsilon\hat{D}_W \tag{18}$$

Where, υ represents the constant drift, $\hat{D}_W$ is the unity vector with the same direction as that of the wind. As the nymphs do not possess wings, their motion is highly correlated to the direction in which the wind blows. The components $\wp_i$, H_i and I_i are substituted in Equation 14, we get:

$$\wp_i = \sum_{j=1,}^{N} \eta(\ell_{ij})\ell_{ij} - a\hat{c}_G + \upsilon\hat{D}_W \tag{19}$$

Where, $\eta(\kappa) = fe - \kappa / 1 - e - \kappa$,N denotes the number of grasshoppers.

For providing a balance exploration and exploitation to obtain a precise approximation of global optimum, the QOGA is formulated as:

$$\wp_i = \eta\left(\sum_{j=1,}^{N} \eta \frac{up_b - lw_b}{2} \varphi\left(\left|\upsilon_j - \upsilon_i\right|\right) \frac{\upsilon_j - \upsilon_i}{\ell_{ij}}\right) + \upsilon\hat{D}_W \tag{20}$$

Where, up_b and lw_b illustrates the upper bound and lower bound in the b^{th} dimension, $\eta(\kappa) = fe - \kappa / 1 - e - \kappa$ is the value of the b^{th} dimension in the target (best solution found so far), and η is a decreasing coefficient to shrink the comfort zone, repulsion zone, and attraction zone. However, we do not consider gravity H_i and assume that the wind direction I_i is always towards a target $\hat{D}_W$.

Equation (20) shows that the next position of a grasshopper is defined based on its current position, the position of the target, and the position of all other grasshoppers. Note that the first component of this equation considers the location of the current grasshopper with respect to other grasshoppers.

In order to obtain a better quality solution, a population is chosen which is opposite to the current population and both are preceded simultaneously. A variable quasi-opposite value of a candidate solution is a value, which is arbitrarily taken between the midpoint of the search space and the mirror point of the variable. The quasi-opposite population is generated as follows:

$$\wp_{ij}^{q} = \Lambda_{rand}(a,b) \tag{21}$$

$$a = \frac{\wp_{ij}^{\min} + \wp_{ij}^{\max}}{2} \tag{22}$$

$$b = \wp_{ij}^{\min} + \wp_{ij}^{\max} - \wp_{ij} \tag{23}$$

Where, $\wp_{ij}$ is the j^{th} variable of i^{th} a candidate solution, $\wp_{ij}^{\min}$ and $\wp_{ij}^{\max}$ are the minimum and maximum values of $\wp_{ij}$, $\wp_{ij}^{q}$ is the quasi opposite value of $\wp_{ij}$.

Thus, based on the QOGA, the optimal path for aggregated data is transferred towards the base station from CH. Thus, the overall outline of the proposed WMBA is illustrated in figure 3 in the form of pseudo-code.

Input: Objective Function $CH_{fitness}(\wp_i) = \Psi_1\Phi_{RES} + \Psi_2 D_{CH,BS} + \Psi_3 N_d$
Output: optimal path selection between CH and BS

Begin

Initialize $\Theta_{\max}, \Theta_{\min}, \wp_{ij}^{\min}, \wp_{ij}^{\max}$ and max_iteration
Initialize the population of solution $\wp_{ij}$ and $\wp_{ij}^{q}$
Evaluate each solution in both the population using,
For i=1 TO N
For j=1 TO N
$\wp_{ij} = [\wp_1 \ldots . \wp_n]$
$\wp_{ij}^{q} = \Lambda_{rand}(a,b)$
Select the best solution
End for
End for
While $(stopping\ criteria\ not\ satisfied)$ **do**

Update the Θ using,
$$\Theta = \Theta_{\max} - l\frac{\Theta_{\max} - \Theta_{\min}}{L}$$
For each solution **do**
Mapping and **Setting** the separation interval between the grasshoppers is fixed as (1, 4)
Update the current location of the grasshopper using,
$$\wp_i = \eta\left(\sum_{j=1,}^{N}\eta\frac{up_b - lw_b}{2}\varphi(|\upsilon_j - \upsilon_i|)\frac{\upsilon_j - \upsilon_i}{\ell_{ij}}\right) + \upsilon\hat{D}_W$$
Update $\wp$ it there is any better solution in population
$\wp = \wp + 1$
If $(\wp > \wp_{ij})$
Return $\wp$ (optimal path)
Else
Alter opposition populations using
$$a = \frac{\wp_{ij}^{\min} + \wp_{ij}^{\max}}{2}$$
$$b = \wp_{ij}^{\min} + \wp_{ij}^{\max} - \wp_{ij}$$
End for
End for
End while
End begin

Figure 3: Pseudo code for QOGA

4. Results And Discussion

The proposed framework is validated based on various metrics along with various existing methodologies to analyse the energy efficiency of the work for the Wireless sensor network. The work is performed based on a collection of 250 sensor nodes in a sensing area.

4.1. Performance Analysis

The proposed work is experimented based on the proposed methodology for CH selection using WMBA and optimal routing of the CH to the BS using QOGA. Based on the performance metrics such as energy consumption, packet delivery ratio, throughput, network lifetime, first node dead, last node dead etc the experimentation is carried out.

4.1.1. Performance analysis of the proposed WMBA for optimal CH selection

The proposed optimal CH selection using WMBA is analysed based on Network Lifetime, Energy Consumption, Throughput, first node dead and last node dead, along with the existing methodologies such as bat algorithm (BA), Squirrel Search Optimization (SSA), Ant Colony Optimization (ACO), and Whale Optimization Algorithm (WOA).

4.1.1.1. Evaluation of proposed WMBA CH selection based on First and Last Node Dead

Based on the number of rounds, the alive node (up to last node dead) and the dead node (first node dead) are computed for the WMBA optimal CH selection. The evaluation is tabulated in table 1.

Table 1: Evaluation of proposed WMBA CH selection based on number of rounds

Techniques	**BA**	**SSA**	**ACO**	**WOA**	**Proposed WMBA**
First dead nodes	**56**	**289**	**350**	**1000**	**1400**
Last Dead nodes	341	789	800	1200	1756

Table 1 illustrates the alive nodes and dead nodes after a certain number of rounds. Based on the CH selection, the alive nodes and dead node vary for different rounds; that is, if the selected CH is far away from BS, then there might be a loss of energy quickly after certain rounds; otherwise, if the selected CH is optimal then the energy consumption can be reduced up to certain rounds. From the evaluation, it can be stated that in the proposed WMBA CH selection, the first nodes die at 1400 rounds and the overall nodes get dead at 1756 rounds, whereas in the existing methodology such as in BA first nodes die at56 rounds and the overall nodes get dead at 341 rounds, in SSA first nodes is dead at 289 rounds and the overall nodes get dead at 789 rounds, in ACO first nodes is dead at 350 rounds and the overall nodes get dead at 800 rounds, and in WOA first nodes is dead at 1000 rounds and the overall nodes get dead at 1200 rounds. The existing methodology constraints high energy loss while transmitting the data from CH to BS, which causes their nodes to die quickly compared to the proposed methodology. The graphical representation of the proposed method and the existing methodology are represented in figure 4.

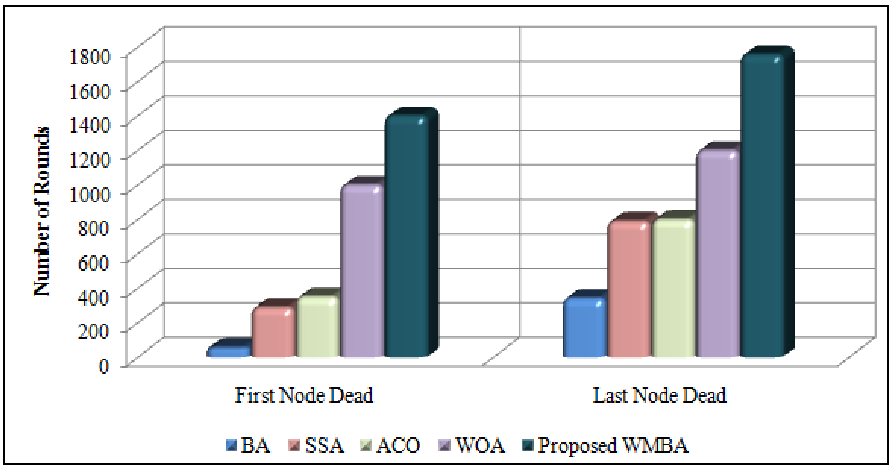

Figure 4: Demonstration of proposed WMBA based on first node dead and last node dead

Figure 4 illustrates the alive nodes and dead nodes based on the CH selection for various rounds. From the graph, it is clearly understood that the proposed WMBA is performing better by minimizing the energy loss at the time of transmitting data from CH to BS; whereas, the existing methodology lags behind the proposed method and leads to significant energy loss.

4.1.1.2. Evaluation of proposed WMBA CH selection based on Energy Consumption

Energy consumption illustrates the maximum utilization of energy by the CH to transmit the data to BS. Based on various numbers of rounds such as 0, 400, 800, 1200, 1600, and 2000 the energy consumption is analyzed for the proposed WMBA and various existing algorithms such as BA, SSA, ACO, and WOA. The evaluation of the energy consumption is carried out in table 2

Table 2: Energy Consumption Evaluation based on number of rounds for the proposed WMBA

Techniques/No of Rounds	**400**	**800**	**1200**	**1600**	**2000**
Proposed WMBA	215	495	635	875	980
BA	310	600	890	1155	1295
SSA	367	663	871	1297	1384
ACO	440	740	1000	1323	1504
WOA	504	805	1178	1413	1636

From table 2, it can be evaluated that the energy consumption for the proposed WMBA tends to achieve an energy consumption of 215J at the end of round 400, and it tends to consume less amount of energy up to the maximum round of 2000 by obtaining a 980J of energy. But, the existing methodologies such as BA, SSA, ACO, and WOA tend to achieve a range of 310J to 504J of energy consumed at the end of round 400, and at the end of round 2000, it obtains an energy range of 1295J to 1636J. The existing methodologies consume more energy between the rounds of 400 to 2000, which is due to the improper selection of the CH with respect to BS. Thus, the proposed WMBA achieves better energy consumption than the existing methodologies due to its robust selection of CH. The graphical representation of Energy consumption is illustrated in figure 5,

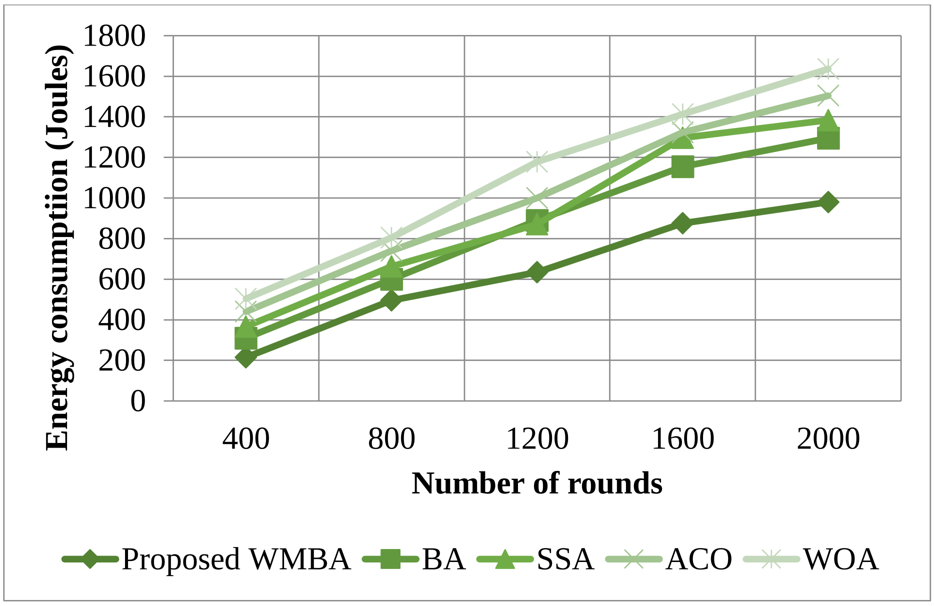

Figure 5: Demonstration of proposed WMBA based on energy consumption

Based on the energy consumption, the graphical analysis has been done for the proposed WMBA along with various existing methodologies such as BA, SSA, ACO, and WOA in figure 5. From the analysis, it is known that the selection of CH tends to consume less energy for the various numbers of rounds as compared with the existing methods.

4.1.1.3. Evaluation of proposed WMBA CH selection based on Throughput

Throughput states the number of data packets sent from the sensor node towards the base station over the cluster round. The amount of throughput signifies energy-efficient utilization of available network resources. Throughput presents the quality of the network.

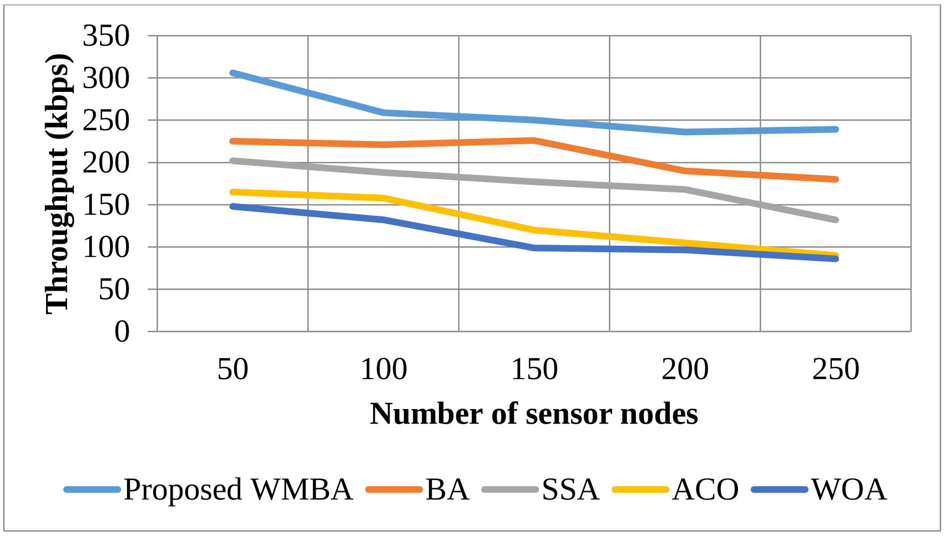

Figure 6: Demonstration of proposed WMBA based on throughput

Figure 6 illustrates the throughput value achieved for the proposed WMBA and the existing methodologies such as BA, SSA, ACO, and WOA. The graphical analysis states that the proposed WMBA achieves a throughput value of 258 kbps for an average sensor node of 150, whereas the existing methods such as BA, SSA, ACO, and WOA achieve an average throughput value of 209kbps,174kbps,127kbps and 112kbps respectively. The high throughput value indicates a minor loss of data between the CH and BS; whereas, the low throughput value indicates a significant loss of data between the CH and BS. According to that, the proposed method achieves a better throughput value as compared to the existing methodologies and remains to be the most optimal method for selecting the CH.

4.1.2. Performance analysis of the proposed QOGA for Optimal Routing

The proposed QOGA for optimal routing between the CH and BS is analyzed based on various performance metrics, such as energy consumption, network lifetime, and packet delivery ratio. After that, the proposed work is compared with the various existing methodologies such as grasshopper optimization (GO), particle swarm optimization (PSO), Fruit fly optimization algorithm (FFOA), and Low energy adaptive clustering hierarchical (LEACH). The evaluation of the metrics is evaluated in upcoming sections.

4.1.2.1. Evaluation of the proposed QOGA optimal path selection based on Energy consumption

Energy consumption of the routing protocols is said to be directly proportional to the transmission distance in WSN. Thus, the transmission distance should be optimal that is the shortest path in order to consume less energy. The evaluation of the metrics is tabulated in table 3.

Table 3: Energy Consumption Evaluation based on number of rounds for the proposed QOGA Optimal path selection

Techniques/Number of Rounds	**400**	**800**	**1200**	**1600**	**2000**
Proposed QOGA	210	485	630	870	975
GO	305	590	885	1150	1295

PSO	362	658	866	1283	1379
FFOA	435	735	995	1318	1498
LEACH	499	800	1173	1408	1631

The energy consumption for the proposed QOGA is analyzed with various existing methodologies, such as GO, PSO, FFOA, and LEACH based on the number of rounds in table 3. From the table, it can be stated that the proposed QOGA achieves an energy consumption of 210J for the minimum round of 400, and it tends to obtain an energy level of 975J for the maximum round of 2000. But the existing methodologies, such as GO, PSO, FFOA, and LEACH, tend to achieve an energy range of 305J to 499J at the end of round 400, and at the end of round 2000, it obtains an energy range of 1295J to1631J. The existing methodologies consume more energy between the rounds of 400 to 2000, which is due to the improper selection of the transmission path between CH and BS. Thus, the proposed QOGA achieves better energy consumption as compared to the existing methodologies due to its optimal selection path between CH and BS. The graphical representation of Energy consumption is illustrated in figure 7.

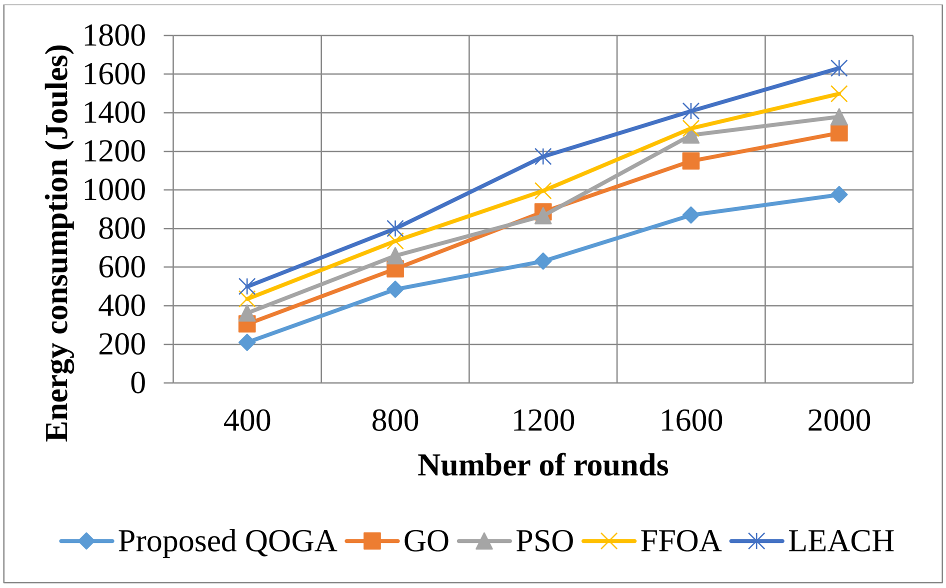

Figure 7: Graphical Demonstration of proposed QOGA based on energy consumption

Based on the energy consumption, the graphical analysis has been done for the proposed QOGA along with various existing methodologies such as GO, PSO, FFOA, and LEACH in figure 7. From the analysis, it is known that the proposed method tends to select an Optimal path and consumes less energy for the various number of rounds as compared with the existing methods.

4.1.2.2. Evaluation of the proposed QOGA optimal path selection based on network lifetime

Network Lifetime is evaluated based on the first dead nodes and the last dead nodes for a number of rounds based on the different number of sensor nodes. The relation between the network lifetime and optimal path selection is that if the selected path between CH and BS is short, then there might be low consumption of energy, and the lifeline of the network will be high, but if the selected path distance is maximum, then the consumption of the energy will be high and the network lifetime will be short and will be collapsed. The graphical analysis of the Network lifetime is illustrated in figure 8.

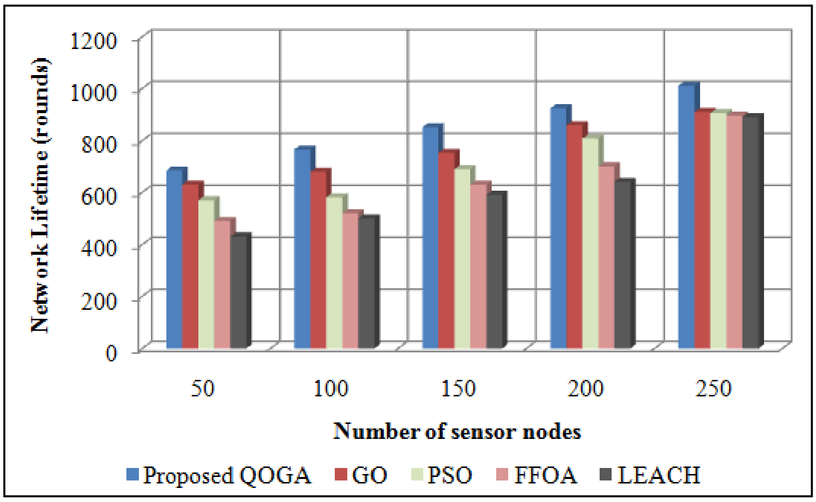

Figure 8: Graphical Demonstration of proposed QOGA based on Network Lifetime

Figure 8 graphically analyse the proposed QOGA based on various existing methodologies such as GO, PSO, FFOA, and LEACH for the network lifetime. Optimal path selection between the CH and BS should be minimum or shortest in order to extend the lifetime of the network and according to that the proposed QOGA achieves the dead of the first node of 50 after the completion of round 685 and the last sensor node of 250 dies after round 1010 .from the first node and last node dead it can be stated there is a slight energy loss between the sensor nodes which represents a perfect path optimization for transmitting data. But, when the existing methods, such as GO, PSO, FFOA, and LEACH are considered, there is a huge loss of energy due to its imperfect optimal pathing between CH and BS. Thus the proposed method achieves an optimal routing between CH and BS as compared to the existing algorithms.

4.1.2.3. Evaluation of the proposed QOGA optimal path selection based on packet delivery ratio

The number of packets delivered to the base station is also an important metric for obtaining energy-efficient WSN. The packet delivery ratio is computed for the proposed QOGA which illustrates that the more balanced the energy distribution in the network, the more the packets is delivered to BS. The relation between the optimal path selection and PDR is that if the path selected is minimal then there is a balanced and energy distribution among the network otherwise there is an imbalanced energy distribution among the network. The detailed evaluation of PDR for different sensor node is graphically analysed in figure 9.

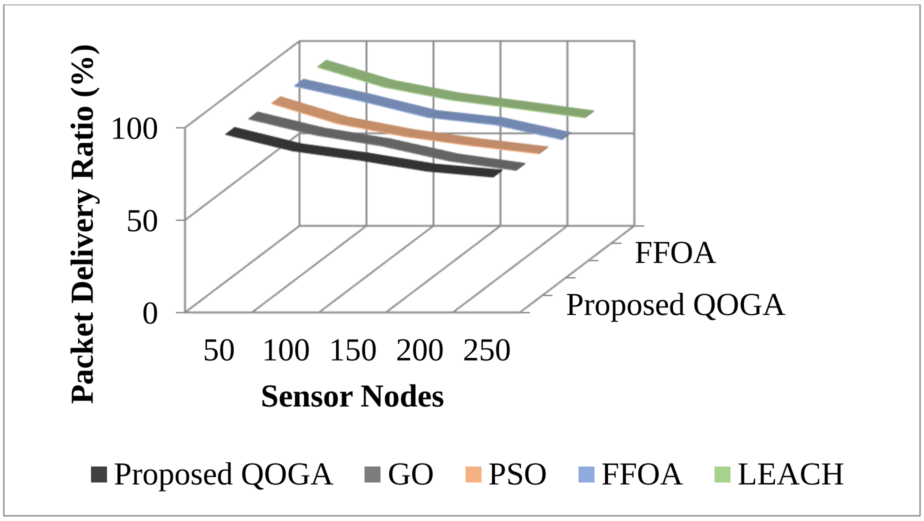

Figure 9: Graphical Demonstration of proposed QOGA optimal path based on PDR

Based on various existing methodologies such as GO, PSO, FFOA, and LEACH, the proposed QOGA algorithm is analysed graphically in figure 9 for the PDR metrics. From the graph, it can be analysed that the number of packets delivered by the proposed QOGA for 50 sensor nodes is 93.56% and for 250 sensor nodes is 70.45%. Thereafter, GO obtains a good PDR of 92.54% for 50 sensor nodes and 64.68% for 250 sensor nodes. The least performance is obtained by the PSO algorithm, which achieves a PDR of 91.45% for 50 nodes and

64.26% of PDR for 250 sensor nodes. Thus, the proposed QOGA achieves a better PDR value due to optimal CH selection and path selection between the CH and BS. Thus, the proposed method achieves a robust optimal routing between CH and BS as compared to the existing algorithms.

5.Conclusion

WSN are widely used in different fields. Optimal utilization of energy is an essential factor that has to be considered for improving the network lifetime of WSN. The work has developed an optimal CH selection using WMBA and optimal path selection using QOGA between CH and BS for balanced and low consumption of energy under the MKMA clustering process. The experiments show that the proposed methodology achieves better network lifetime by obtaining a dead of first sensor node at 1400 round and overall dead node at 1756 round, which illustrates a better energy consumption of 975J for the entire round of 2000 along with better delivery of packets to BS by achieving a PDR of 93.56% and remains to be energy efficient as compared to the existing state of art methods. The work must be carried based on balancing of energy by using optimized intelligent algorithms in the future

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