A Trust and Optimal Energy Efficient Data Aggregation Scheme for Wireless Sensor Networks Using Qgaoa

Nandha kumar (nandhakumarresearch@gmail.com)
Erode Arts and Science College https://orcid.org/0000-0002-4756-3156
P. Srimanchari
Erode Arts and Science College

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A TRUST AND OPTIMAL ENERGY EFFICIENT DATA AGGREGATION SCHEME FOR WIRELESS SENSOR NETWORKS USING QGAOA

Nandha Kumar [1, *], Srimanchari [2]

[1]Research Scholar, Department of Computer Science, Erode Arts and Science College, Erode, Tamilnadu, India.

[2] Assistant Professor, Department of Computer Science, Erode Arts and Science College, Erode, Tamilnadu, India.

nandhakumarresearch@gmail.com

Abstract: In recent years, Wireless Sensor Networks (WSNs) have become a key technology for monitoring and tracking applications in a wide application range. A wireless sensor network (WSN) senses the environment, collects data, and sends it to a base station (BS) for analysis. A fundamental challenge in designing WSNs is maximizing their lifetimes, especially when energy is limited. Managing trust in the WSN is also a difficult task because trust is used when collaboration is critical to achieving reliable communication. As a result, this paper proposed a secure and energy-aware data aggregation and optimal routing scheme for WSNs based on the Quantum behaviour and Gaussian Mutation based Archimedes Optimization Algorithm (QGAOA). The proposed system comprises three parts: cluster formation, cluster heads (CHs) selection, and optimal routing. Initially, clusters are formed using the Voronoi-included K-means clustering algorithm (VKMCA). Then CHs are selected, and optimal routing is selected using QGAOA. Simulations are carried out to analyze the performance effectiveness of the proposed system with existing related techniques. The results revealed that the proposed system outperformed existing techniques regarding network lifetime (NLT), energy consumption (ECP), throughput, delay, and packet delivery rate (PDR) factors.

Keywords: Wireless Sensor Network (WSN), Base Station (BS), Cluster Head (CH), Voronoi based K-Means (VKM), Archimedes Optimization Algorithm (AOA).

1 Introduction

The revolution in dependable, low-cost, and effectual sensor technology has advanced several WSN-based applications. WSNs have recently evolved into one of the world's most effective strategies [1]. WSNs are wireless network' subsets developed to gather information about their surroundings employing sensors such as cameras, thermometers, and speedometers [2]. Innumerable monitoring applications have been imagined using futuristic WSN technologies [3, 4]. A WSN is made up of a BS, a sink, and sensor nodes (SENs) [5, 6]. The nodes are widely dispersed, and their jobs are to transmit sensed parameters to the sink node [7]. The intermediate nodes use intuitive energy to deliver data, resulting in a higher ECP rate and accelerated network partitioning. Also, these SNs have limited resources, such as limited memory, battery power, and processing ability [8]. One approach for circumventing these constraints is to employ intra-network data aggregation (DAG), which decreases the amount of data transmitted to the BS [9].

The DAG method reduces the count of packets sent via the networks' at the data acquisition time. The DAG process initially collects the data from the SENs to perform data transmission. At the time of transmission, it identifies and removes the redundant data packets of the SENs to improve the ECP of the nodes [10, 11]. In the WSNs, the DAG process is carried out as a clustering process that groups similar SENs in the network to decrease the ECP and improves the lifetime [12]. Each group of SENs has a CH leader responsible for collecting and transmitting the data from their group members and sending it to the BS [13]. Nevertheless, CHs devour higher energy owing to their processing, computational, and transmission capacities in DAG, which drains the battery life and decreases the network lifetime. So, clustering and DAG are the major research problem in WSNs [14]. Energy efficient DAG and routing was one of the practical solutions to overcome the problem of higher ECP and lower NLT of the SENs [15].

When performing cluster-based routing in WSNs, the CHs gather the data from their group members and forward it to the BS via single-hop or multi-hop routing. In the process of routing, there is a possibility of network and data attacks from intruders, which leads to packet drops, incorrect routing, data hacking, and redundant routing [16]. So it is necessary to develop a secure and energy-efficient DT system in WSNs with the help of clustering and routing. Despite many routing algorithms in the literature, the security challenges are only considered in some existing protocols. Therefore, this paper develops a trust and energy-aware optimal routing system for WSNs which integrates clustering, CH selection, and routing techniques towards achieving reliable communication with fair energy load balance in WSNs. The proposed algorithm's main advantage is increased security and performance with less ECP. The main objectives of the proposed work include given below:

- At first, the clustering process is carried out using the VKMCA approach to decrease the ECP of the SENs and enhance the NLT.
- The reliable and energy-efficient CHs are selected optimally using the QGAOA algorithm. Therefore, the malicious activity of the nodes is avoided during the CH selection, which decreases the packet drops and increases the network security.
- To securely send the CHs collected data to the BS, trust-based optimal multi-paths are chosen using QGAOA with multi objectives to minimize the nodes' ECP.

The remaining paper is organized as follows: Section 2 summarizes the related work about the existing research done in secure energy-aware routing in WSN. A clear explanation of the proposed work is provided in section 3. Section 4 explains the results and discussion of the developed model, and Section 5 concludes the paper and future work.

2 Related Works

Recently, many kinds of energy-efficient CHs selection and routing techniques have been proposed for WSNs. This section presents an in-depth survey of those recently proposed models and their drawbacks to overcome when performing DT in WSNs.

M.Vasim Babu *et al*. [17] presented the technique of distributed autonomous fashion with fuzzy if-then rules to perform clustering and CH selection in WSN. After

CHs collect the data from the cluster members, they transmit the packets from them to the BS by selecting the optimal paths. An adaptive source location privacy preservation approach based on routes was selected to perform the routing of CHs data. The approach additionally used principal component analysis to aggregate the data securely from the CHs to provide security to the nodes' data. The outcomes proved that the model performed better than the previous related schemes. Huaying Yin *et al.* [18] suggested an ad-hoc on-demand distance vector protocol and multi-path routing technique to provide energy-efficient and trust-based routing in WSN. The framework selected optimal and secure routes for DA by considering trust, energy, count of hops, and distance. The model demonstrated superior results by identifying the malicious behaviour of the nodes with lower energy and higher NLT.

Akhilesh Panchal *et al.* [19] recommended energy aware distance-based CH selection and routing scheme to increase the lifespan of WSN. The scheme used fuzzy c-means clustering approach to cluster the SENs and select the CHs in the network. The clusters and CHs selection process was based on metrics such as nodes' energy and distance from BS to cluster centroids. The simulation experiments confirmed that the framework attained the best results regarding lifetime and energy compared to other schemes under various scenarios. Richa Sharma *et al.* [20] presented a whale optimization algorithm to carry out secure and energy-efficient data transformation in WSNs. The model selected the secure SENs for DA by considering the node's energy, average cluster distance, counts of data packets transmitted by a node, delay, and node density. Then the scheme forwards its collected data to the BS via the selected CHs. The outcomes revealed that the schemes surpassed existing protocols.

Maryam Hajiee *et al.* [21] introduced an energy-aware trust and opportunity-based multipath routing mechanism for WSNs. The method used multipath routes to deliver the node's data to the BS by considering inter-cluster and intra-cluster multi-hop communication. The routs for DT were chosen optimally based on the parameters such as trust, energy, QoS, distance, and count of hops. The outcomes confirmed that the presented schemes worked better than previous schemes related to trust and energy for DT. B. Mohankumar and K. Karuppasamy [22] presented an ant colony optimization (ACO) technique to perform secure and energy-efficient optimal DT in WSNs. Initially, ACO was implemented to choose the CHs for DA to increase the network's lifespan. Then to send the information of the SENs from the chosen CHs to the BS through the optimal paths, a hybrid genetic particle swarm optimization technique was utilized. The technique selected the optimal paths by considering the parameters such as processing capability, energy and bandwidth. The approach showed a better performance compared to existing models.

Each of the previously mentioned research works has advantages in achieving acceptable results. Nevertheless, some existing techniques do not prioritize essential measures such as efficient resource usage, trusted routes, and ECP. Moreover, in prior work, the CH was selected randomly, causing lower system performance; as the number of nodes increases, the system may struggle because more energy is consumed to handle the CH. Furthermore, while some existing systems achieved better results than the other methods, the results revealed that they had high computational and communication costs. The WSNs manage the confidential information of the SENs in hostile and unattended platforms, so it is necessary to focus on the security components to safeguard the network of nodes from several attacks. Some works focus on trust and energy efficient based routing for WSNs. However, they were only suitable when the nodes had the same and balanced ECP. When performing DT, the ECP of the nodes will vary, and the mentioned techniques are not suitable now. In addition, the traditional optimization techniques used in the previous models for CHs selection and routing have problems of local-optimal issues, premature convergence and population diversity. So the solutions lead to the improper selection of CHs and paths for DT. This decreases the performance of the network. So to overcome such drawbacks, this paper develops a trust and energy-efficient multipath routing system for WSNs using a novel clustering and routing mechanism based on the QGAOA model.

3 Proposed Methodology

Providing secure routing in WSN is a difficult task, as evidenced by many research papers that have been presented. The WSN routing protocol still has a research gap. This paper is divided into three stages: cluster formation, CHs selection, and optimal routing. To begin, the clustering process employs the VKMCA clustering approach, which groups similar nodes in the network. Then, the CHs are chosen, and the best routing path is chosen to transmit data packets using the QGAOA securely. The QGAOA method uses the control messages of the ad hoc on-demand distance vector (AODV) routing protocol when performing routing. Figure 1 shows the block diagram of the proposed method.

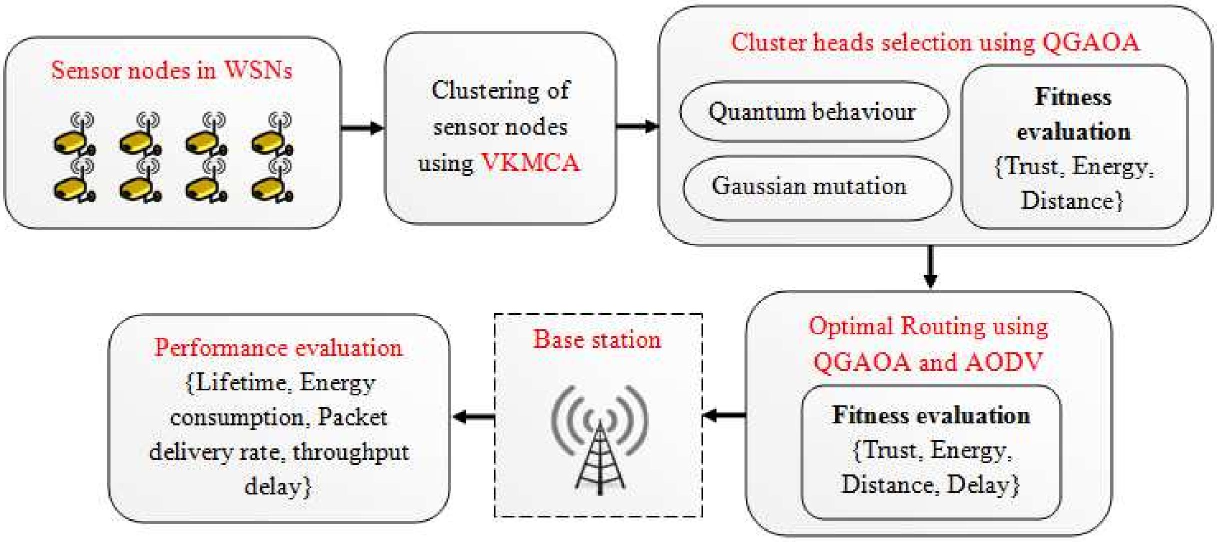


Figure 1: Proposed Architecture

3.1 Cluster Formation

Clustering is an important method to lower the ECP and extend the lifespan of the SENs in the network. It entails clustering SENs and electing CHs for each cluster. The VKM algorithm is proposed here for cluster formation, which clusters the network's similar nodes based on their distance. K-Means is an excellent and efficient clustering algorithm. Sensors are positioned in the sensing region to identify an activity, and the sensed data must be transferred to the BS to acquire knowledge. Transferring sensed data from SENs to BS may consume more energy to send and receive data, lowering NLT. Consequently, the VKM algorithm is used in the proposed system. It is a prototype-based method that alternates between two significant stages, allocating observations to clusters and computing cluster centres till a stopping criterion is met.

Firstly the algorithm applied the method of Voronoi to generate a Voronoi diagram (VD) for the network. The construction of VD is done by dividing the sensed area of the network as subareas, each controlled by one SEN, and the subareas are called Voronoi cells. After generating VD, the clustering process is carried out using the K-Means clustering algorithm (KMCA), and then DT and data collection phases are applied. This incorporation of the Voronoi method in conventional KMCA is termed VKMCA. Doing this diminishes the network's data traffic and the distances that data must be transmitted over, enhancing the network's lifespan. The steps included in the VKM are described as follows:

Step 1: Assume all SENs in the network are stationary, and the node's position in the network is described by s and t coordinates. Compute the distance between the nodes using the Euclidean distance (ED) to construct a Voronoi diagram, which is given in equation (1).

$$EucliDist(x, y) = \sqrt{(s_x - s_y)^2 + (t_x - t_y)^2} \quad (1)$$

Where, $EucliDist(x, y)$ represents the ED between node (x) and set of all neighbor nodes (y). A set of distinct points (sites) in the plane, noted by z which represents a set of points as $z_1, z_2, \ldots\ldots z_n$. Then subdivide the plane into n cells so that each cell contains exactly one site. An arbitrary point (s,t) is in a cell corresponding to a site z_e with coordinates (s_{ze}, t_{ze}) if and only if for all z_f with $f \neq e$, $1 \leq e, f \leq n$. That is, the ED from (s,t) to any other site is greater than the distance from (s,t) to z_e.

$$\sqrt{(s - S_{ze})^2 + (t - T_{ze})^2} < \sqrt{(s - S_{zf})^2 + (t - T_{zf})^2} \quad (2)$$

Step 2: Next, consider $k_c^{''}$ initial centroid for clustering the SENs into '$k_c^{''}$' cluster.

Step 3: Compute the distance from each node to all centroids using the ED formula and assign it to the centroid nearest to it. By this "$k_c^{''}$" initial clusters are formed.

$$NewDist(dp, cr) = \|dp_u - cr_v\|^2 \quad (3)$$

Where, $\|dp_u - cr_v\|^2$ indicates the ED between a data point dp_u and the cluster center cr_v.

Step 4: Re-estimate the positions of cluster centroids and check for the change in position from the previous one.

Step 5: Go to step 3 if the position of any centroid changes. Otherwise, the clusters are finalized, and the clustering process is completed. By this, the clustering of nodes into '$k_c^{''}$' number of clusters is done.

3.2 Cluster Heads Selection

Once the SENs are grouped, CHs for each cluster group are selected optimally using the QGAOA. The CHs are responsible for collecting the data from their cluster members and transmitting the collected data to the BS. The proposed model selects the optimal CHs by considering three parameters: the node's trust, residual energy, and distance. The Archimedes Optimization Algorithm (AOA) is a population-based algorithm, whereas the immersed object is assumed as the candidate. Like other Meta heuristic-based populations, this approach starts with some amount of arbitrary values that are distributed uniformly in a possible range. It starts its search with an initial population of random volume, density, and acceleration, permitting it to balance localization precision and speed. Nevertheless, even so, population diversity significantly affects the AOA since it enables a population to have a more vital exploration capability while also being less likely to fall into local optima. As a result, this paper adopts QGAOA to increase the traditional AOA's diversity. The in-depth steps of QGAOA steps are given below.

Step 1: Initialize the population of the QGAOA using equation (4):

$$A_p^{''} = lb_p^{''} + R_{xrand} \times \left(ub_p^{''} - lb_p^{''}\right), \qquad p = 1,2,3,......M \tag{4}$$

Where, $A_p^{''}$ refers to the p^{-th} cluster in a population of M clusters, and $ub_p^{''}$ and $lb_p^{''}$ represents upper and lower bound of the search space respectively. The term R_{xrand} indicates the random values [0, 1]. The volume ($\overline{VC}$), density ($\overline{DC}$) and acceleration ($\overline{AC}$) of each cluster can be initialized as follows:

$$\begin{aligned} \overline{DC}_p &= R_{xrand} \\ \overline{VC}_p &= R_{xrand} \\ \overline{AC}_p &= lb_p^{''} + R_{xrand} \times \left(ub_p^{''} - lb_p^{''}\right) \end{aligned} \tag{5}$$

Step 2: Select the cluster with the best fitness value ($F_{xfit}^{''}$) based on the distance ($D_{xdis}^{''}$), energy ($E_{xenr}^{''}$), and trust ($T_{xtst}^{''}$), which is multiplied by η, λ, and κ weight value. The CH is selected based on the best fitness value, which is the cause of maximal energy, minimal distance, and maximal trust.

$$F_{xfit}^{''} = \eta . E_{xenr}^{''} + \lambda . D_{xdis}^{''} + \kappa . T_{xtst}^{''} \tag{6}$$

The parameters, such as energy, distance, and trust, are divided by a normalization factor, which is shown in equations (7) to (10).

- ***Energy***

The sensor node's residual energy can be calculated by adding the energy depleted while the node was in each state. The energy constraint is calculated using the following formula:

$$E_{xenr}^{''} = \frac{1}{T_{tch}} \sum_{n=1}^{T_{tch}} \left(E_{xenr}^{''}\right)_n \tag{7}$$

Where, T_{tch} denotes the total number of CHs.

- ***Distance***

The distance between two nodes, according to the distance of CH, is known as the node's distance. This distance must be very short in order to communicate effectively. The distance between the n^{-th} CH and o^{-th} its neighboring node is mathematically expressed as follows:

$$D^{"}_{xdis} = \frac{1}{T_{tch} * N_{nch}} \sum_{n=1}^{T_{tch}} \sum_{o=1}^{N_{nch}} \left[1 - \frac{\left(D^{"}_{xdis}\right)_{no}}{N_{nch}} \right] \tag{8}$$

Where, N_{nch} refers the total neighboring nodes.

- ***Trust***

The trust value is a node's degree of trust in receiving services compared to neighbouring nodes. It should be high for the node to act as a CH. The trust factor is formulated as follows:

$$T^{"}_{xtst} = \frac{1}{T_{tch} * N_{nch}} \sum_{n=1}^{T_{tch}} \sum_{o=1}^{N_{nch}} \left(T^{"}_{xtst}\right)_{no} \tag{9}$$

The above equation signifies that the trust of the node is formulated as the trust of the n^{-th} CH and o^{-th} its neighboring node, which is the average of the three trust factors, namely, recent (T^{recent}_{xtst}), direct (T^{direct}_{xtst}), and indirect trust ($T^{indirect}_{xtst}$). The node linked directly to the neighbour nodes in both capacity and trustworthiness for completing the request is named direct trust. The node relies on indirect trust for two-hop DT, which indicates that the node should rely on neighbour nodes indirectly. In the trusted class, the node can identify whether or not a particular node is reliable and coherent. The recent trust is a combo of direct and indirect trust that is merged by employing weighing factors, and it perceives the target node's recent behaviour. The trust between the nodes "n" and "o" computed as,

$$T^{"}_{xtst} = \frac{T^{recent}_{xtst} + T^{direct}_{xtst} + T^{indirect}_{xtst}}{3} \tag{10}$$

Step 3: Calculate the transfer operator (O_{xto}) and the density decline factor (D_{xdf}) to balance the local and global convergence capability of QGAOA.

$$\begin{aligned} O_{xto} &= \exp\left(\frac{q - q_{\max}}{q_{\max}}\right) \\ D_{xdf} &= \exp\left(\frac{q_{\max} - q}{q_{\max}}\right) - \left(\frac{q}{q_{\max}}\right) \end{aligned} \tag{11}$$

Where, the operator O_{xto} increases gradually with time till it reaches 1. The terms q and $q_{\max}$ denotes the iteration count and maximum counts of iterations.

Likewise, D_{xdf} decreases with time that provides a capability to converge in already recognized promising region.

Step 4: Exploration stage

If $\left(O_{xto} \leq 0.5\right)$, perform the exploration phase and the collision between clusters occurs. Then update the acceleration $(q+1)$ by employing equation (12).

$$\overline{AC}_p^{q+1} = \frac{\overline{DC}_{ranm} + \overline{VC}_{ranm} + \overline{AC}_{ranm}}{\overline{DC}_p^{q+1} \times \overline{VC}_p^{q+1}} \tag{12}$$

Where, $\overline{DC}_p$, $\overline{VC}_p$, and $\overline{AC}_p$ indicates density, volume, and acceleration of cluster p. Also, $\overline{DC}_{ranm}$, $\overline{VC}_{ranm}$, and $\overline{AC}_{ranm}$ denotes the density, volume, and acceleration of random material.

Step 5: Exploitation stage

If $\left(O_{xto} > 0.5\right)$, perform exploitation phase and there is no collision between clusters have occurred. Update the acceleration for iteration $(q+1)$ using the below equation.

$$\overline{AC}_p^{q+1} = \frac{\overline{DC}_{best} + \overline{VC}_{best} + \overline{AC}_{best}}{\overline{DC}_p^{q+1} \times \overline{VC}_p^{q+1}} \tag{13}$$

Where, $\overline{DC}_{best}$, $\overline{VC}_{best}$, and $\overline{AC}_{best}$ represents the best cluster density, volume, and acceleration respectively.

Step 6: Normalize acceleration

It is necessary to normalize each particle's acceleration; this defines the step percentage by which each particle will change. Normalized acceleration can be expressed as follows:

$$\overline{AC}_{p-NormAcc}^{q+1} = rb \times \frac{\overline{AC}_p^{q+1} - \min\left(\overline{AC}\right)}{\max\left(\overline{AC}\right) - \min\left(\overline{AC}\right)} + sb \tag{14}$$

Where, rb and sb indicates the range of normalization and set to 0.9 and 0.1 respectively and $\overline{AC}_{p-NormAcc}^{q+1}$ denotes the normalized acceleration of the p^{-th} cluster in the $q+1$ iterations.

Step 7: Update position

Next, the cluster's position (V_p^q) is updated using QB and GM. Initially, GM is applied to enhance the algorithm's population diversity, which is expressed as

$$V_p^{q+1} = \begin{cases} V_p^q + \alpha_1 \times R_{xrand} \times \overline{AC}_{p-NormAcc}^{q+1} \times D_{xdf} \times \left(V_{R_{xrand}} - V_p^q\right) \times \left(\omega(0,1)+1\right), & if\ O_{xto} \le 0.5 \\ V_{best}^q + F_{val}^{"} \times \alpha_2 \times R_{xrand} \times \overline{AC}_{p-NormAcc}^{q+1} \times D_{xdf} \times \left(h_{time} \times V_{best} - V_p^q\right) \times \left(\omega(0,1)+1\right), & otherwise \end{cases} \quad (15)$$

Where, α_1 and α_2 indicates a constant value equal to 2 and 6. The term h_{time} increases with time, and it is directly proportional to O_{xto} and h_{time} is computed as $h_{time} = \alpha_3 \times O_{xto}$ equals to 0.3. The term D_{xdf} refers to the density factor using equation (11). The term $F_{val}^{"}$ describes the upgrade method of the cluster according to its position.

$$F_{val}^{"} = \begin{cases} +1, & if\ u \le 0.5 \\ -1, & if\ u > 0.5 \end{cases} \quad (16)$$

Where, $u = 2 \times R_{xrand} - \alpha_4$ and α_3 and α_4 are used to balance the population's movement direction that avoids the algorithm being trapped in local optimal problem. The term $\left(\omega(0,1)+1\right)$ represents the GM function and follows the Gaussian distribution with a variance of 1 and a mean of 0. The Gaussian distribution ($GDf(V)$) is expressed as follows:

$$GDf(V) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left(-\frac{(V-\mu)^2}{2\sigma^2}\right) \quad (17)$$

Where, σ and μ indicates the variance and mean. The GD function disrupts the current population's information and aids the cluster in rapidly convergent to globally optimal solutions. The fitness values of the current and optimal individuals in the population are compared utilizing quantum theory. In quantum behaviour, the algorithm's population is rotated toward a more appropriate state between two choices employing the rotation gate. As an outcome, the amplitude of its probability increases. The node's fitness with the shortest distance, the higher trust, and the higher energy is chosen as CH. The diversity of the clusters is achieved, and a better fitness value is acquired by changing the position of the cluster sets.

3.3 Optimal Routing

After choosing CHs optimally, the optimal paths to send the cluster members' data to the BS via the CHs are selected. The routes to share the data from the CHs are selected using the optimization model, namely QGAOA. Here, to select the best secure paths for DT, four major parameters are considered in fitness estimation: trust, delay, energy, and distance. The routes obtaining higher fitness (minimum delay, minimum distance, maximum trust value, and maximum energy) in QGAOA path estimation are considered the best paths for DT. The fitness evaluation in QGAOA for optimal path estimation is expressed as follows.

$$F_{xfit}^{"} = \eta.E_{xenr}^{"} + \lambda.D_{xdis}^{"} + \kappa.T_{xtst}^{"} + \rho.L_{xdel}^{"} \quad (18)$$

Where, $E^{''}_{xenr}, D^{''}_{xdis}, and T^{''}_{xtst}$ represents the energy, distance, and trust factor that is calculated using equations (7) to (10). The delay factor is noted as $L^{''}_{xdel}$ that is an essential factor for forwarding data in a time constraint WSNs environment. Each agent in the QGAOA is initialized with the probable routing path between the CHs and the BS. When selecting an optimal path, the QGAOA uses the control messages (CMs) of the ad hoc on-demand distance vector (AODV) routing protocol. The CMs utilized by the QGAOA for optimal path generation are path request (PRE), path reply (PRP), path error (PE), and hello (HLO). Initially, to find a destination node for a source node to forward its data, the PRE packet is broadcasted. Then the next hop node having higher fitness transforms the PRP through the reverse path. The path between the source and destination nodes is generated optimally once the source node receives the message from the destination node. The proposed model is presented with the intent to avoid DDoS attacks in the networks while performing DT. So using a trust-based and energy-efficient model in selecting both CHs and routing paths, a secure DT of the WSNs is achieved without compromising the energy efficiency and lifetime of the network.

4 Results and Discussion

This section analyzes the performance efficiency of the proposed trust and energy efficient routing model (QGAOA) by comparing their results with the existing models. The proposed framework is experimented using a MATLAB simulation tool. The simulation parameters considered in the proposed system are as follows: the number of nodes: 500, network area: 1500x1500m and topology: mesh. The existing models taken for comparison are AOA, Whale Optimization Algorithm (WOA), and Particle Swarm Optimization (PSO). The approach's performance is assessed using metrics such as delay, throughput, ECP, PDR, and NLT. A comparative analysis is performed in two ways here: analysis with attack scenario and analysis without attack scenario.

4.1 Comparative analysis based on with attack scenario

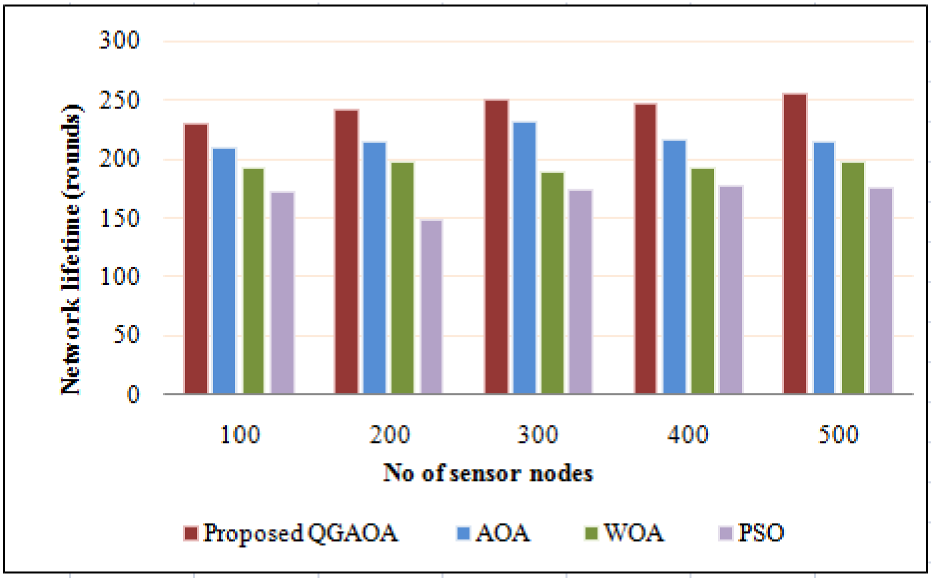
Here the outcomes of the proposed and existing frameworks are compared by considering with DDoS attack situation regarding ECP, delay, throughput, NLT, and PDR.

Table 1: Results of the proposed and existing algorithms

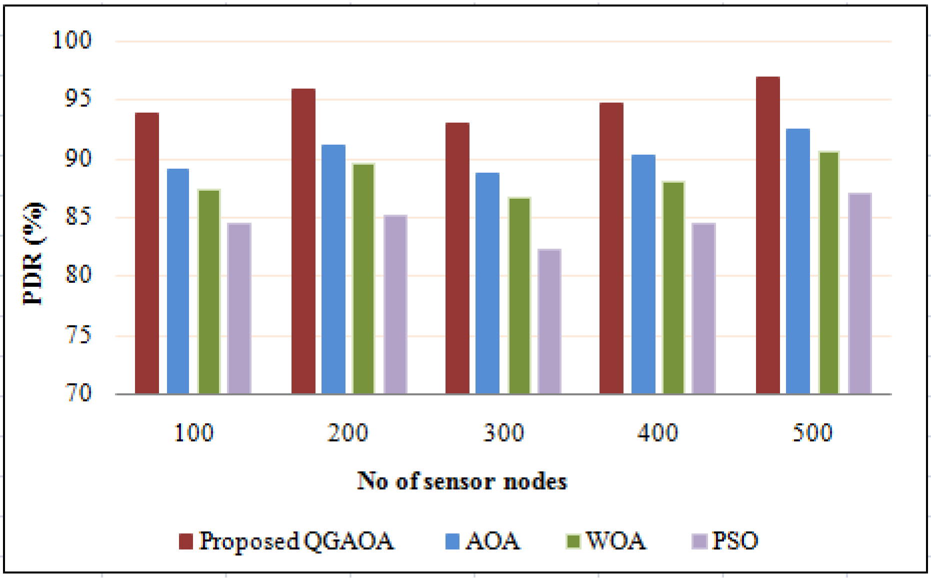
Metrics	Number of nodes	Proposed QGAOA	AOA	WOA	PSO
Energy Consumption (joules)	100	3897.25	4023.98	4467.92	5227.19
	200	4312.93	4712.09	4901.84	5394.87
	300	4901.32	5221.45	5510.63	5803.21
	400	5292.01	5812	6031.84	6684.91
	500	5921.91	6331.07	6591.32	7263.94
Delay (ms)	100	11.34	12.32	13.1	18.64
	200	13.24	15.43	17.21	20.06
	300	14.56	17.68	20.04	27.12

	400	16.21	23.57	25.14	30.87
	500	18.86	25.12	28.32	36.08
Throughput (%)	100	96	84	79	76
	200	97	82	76	74
	300	94	80	78	72
	400	96	78	74	70
	500	95	74	72	66

The techniques' results in ECP, delay, and throughput are tabulated in table 1 by varying the number of SENs from 100 to 500. First, in terms of ECP, the proposed algorithm uses less energy. The proposed QGAOA algorithm consumes 3897.25j for 100 SENs, whereas the conventional AOA, WOA, and PSO consume 4023.98j, 4467.92j, and 5227.19j, respectively. Similarly, the proposed method uses less energy for the remaining sensor node. The proposed QGAOA then achieves the very lowest delay compared to others in terms of delay metric. The average time it takes to route data from the source to the target node is called routing protocol delay. The existing AOA, WOA, and PSO have delays of 25.12ms, 28.32ms, and 36.08ms for 500 SENs, respectively, but the proposed one has the lowest delay of 18.86ms. When the number of SENs increases, the proposed algorithm has a lower delay than the existing algorithms. At last, when analogizing the throughput outcomes, it was observed that the QGAOA provides higher throughput for all counts of nodes in the network compared to other existing frameworks. Next, the NLT and PDR metrics comparison is graphically represented in figure 2.



(a)



(b)

Figure 2: NLT and PDR based comparative analysis

Figure 2 compares the proposed QGAOA algorithm to the traditional AOA, WOA, and PSO algorithms regarding (a) NLT and (b) trust performance metrics. The optimal algorithm is used to select an efficient CH node and an optimal route path, which are then used to increase the NLT and energy efficiency. Figure 2 (a) shows that when the number of SENs is 100, the existing PSO algorithm dies after the 172nd round, whereas the proposed QGAOA has a longer NLT. Similarly, when compared to the conventional AOA, WOA, and PSO for the remaining 200 to 500 SENs, the proposed one has a maximum NLT. PDR is the proportion of data packets acquired by recipients to data packets transferred via the transmitter. It should be higher to prove that the presented approach is efficient for performing DT with lower packet loss. The proposed QGAOA achieves 4.79% greater PDR than AOA, 6.52% greater PDR than WOA, and 9.31% greater PDR than PSO. Compared to existing methods, the QGAOA achieves a high PDR of 93.87% for 100 nodes. It also attains a higher level of PDR for all counts of nodes taken for comparison. These higher values of PDR for the proposed system prove that the system performs efficient DT in the network with a significantly lower amount of packet loss, which also shows that the model maintains better security in DT. So from the results, it was revealed that the proposed QGAOA is suitable for WSNs to perform secure and energy-efficient DT, and it prevents the network from attack.

4.2 Comparative analysis based on without attack scenario

This comparative analysis section is done without an attack scenario for considering the same performance metrics. This comparative analysis is given in table 2. According to table 2, the proposed QGAOA algorithm has ECP, delay, throughput, and NLT of 5712.32j, 20.98ms, 96.68%, 264.9 rounds, and a PDR of 94.87% for without attack scenario, which is comparatively higher than the prevailing AOA, WOA, and PSO methodologies.

Table 2: Comparative discussion for without attack scenario

Metrics	Proposed QGAOA	AOA	WOA	PSO
Energy consumption	5712.32	6231.01	6486.12	7164.12
Delay	20.98	27.12	30.65	38.12
Throughput	96.68	76.12	73.54	67.86
Network life time	264.9	221.45	199.98	177.3
PDR	94.87	90.34	88.45	84.69

5 Conclusion

The most concentrated issue in any network system is security; in the case of WSNs, this is a difficult task. WSN security can be achieved through proper routing. In this paper, secure and energy-aware DAG and optimal routing for WSN use the QGAOA optimization algorithm. The cluster formation, CHs selection, and optimal routing stages are involved in the proposed system. The proposed QGAOA method's performance is compared with traditional algorithms such as AOA, WOA, and PSO based on ECP, delay, throughput, NLT, and PDR metrics for two scenarios (with attack and without attack). In with attack scenario, the proposed system takes minimum ECP and maximum NLT of 4865.08 and 245. Also, the proposed one performs better in the without-attack scenario than the traditional methods. In terms of performance metrics, the results confirm that the proposed system is more scalable and secure than the existing schemes. In future, the work will be extended by including another advanced optimization technique and data security framework for energy-efficient DT to prevent the network from other kinds of attacks.

Compliance with Ethical Standards

Disclosure of potential conflicts of interest

The authors declare that they have no competing interests.

Research involving Human Participants and/or Animals

This article does not contain any studies involving Human Participants and/or Animals performed by any of the authors.

Informed consent

Not Applicable

Availability of data and materials

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

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