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An Optimized Routing Technique in Wireless Sensor Network Using Aquila Optimizer

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Abstract: Wireless sensor networks (WSNs) have become a dominant technology in recent years due to their vast range of applications. However, the creation of energy-efficient WSN remains elusive. Clustering methods have long been employed in WSNs to reduce energy consumption and extend network lifetime, but efficient cluster head (CH) selection and competent routing always pose a major obstacle. This paper, proposes a new routing technique in which CH selection is performed using whale based tunicate swarm algorithm (WTSA) and routing between CHs is implemented using aquila optimizer (AO). In the proposed technique WTSA is used to identify efficient CHs from the WSN network, and remaining nodes join these CHs by assessing the cost function value. CHs residual energy, node degree, distance from base station (BS) and intra-cluster distance are being used to derive this cost function. AO is used for inter-clustering routing between CHs that are far from the BS. With the help of a fitness function, AO is used to cultivate optimal routes between CHs and to weed out ineffective routes. The performance of the proposed technique WTSA-AO is compared with state-of-the-art techniques BOA, PSO-GSA, BERA, WTSA, and LEACH in terms of delay, number of alive nodes, throughput and average energy consumption. The results show that the proposed technique improves the performance of wireless sensor networks by reducing average energy consumption by 8.3 % compared to WTSA and striving to achieve a delay of 0.121 seconds for 200 nodes.

Keywords: Wireless sensor network, Un-equal clustering, Average energy consumption, Whale optimization algorithm, Tunicate swarm algorithm, Aquila optimizer.

1. Introduction

Internets of things, cloud computing, smart cities and big data etc. have significantly increased the need for smart gadgets. Typically, such smart gadgets outfitted with sensors are placed in impassable areas where human access in person is not feasible. The term wireless sensor network (WSN) refers to a network that connects these types of sensors [1,2]. A sensor node (SN) energy source has typically been an AA battery to capture raw-data from the environment, and this raw-data is sent to BS for additional processing. The SN's battery is constantly depleted during sensing and transmission of raw data and replacing these AA batteries is not always practicable in difficult circumstances such as military surveillance, agricultural, health care monitoring, and earth sensing [2]. Furthermore, when raw-data is transmitted directly from nodes to BS, battery usage is higher. As a result, SN energy consumption and utilization represent a significant barrier during the lifetime of a WSN's network. Several battery-saving strategies have been offered in the literature to assist saving battery power. However, Heinzelman [1] methodology low energy adaptive clustering hierarchy (LEACH) is regarded as the most prominent and coherent. LEACH divides the entire network into smaller groupings known as clusters. Each cluster has a CH which is in charge of relaying raw-data obtained from the SN to the BS. Along with raw-data transmission to the BS, the CH is also responsible for raw-data aggregation. The BS ensures a control handover of raw data to the remote server by utilizing an Information and communication technology (ICT) framework. The CH circumscribes the direct communication between SN and BS to extend the network's life and conserve SN battery power. The CH plays an important role in extending the lifetime of the WSN, it is crucial to build up an election and selection system to choose the best CHs in the network [3, 4].

Multi-hop routing is also used between CH in some cases when a cluster is located extremely far from the BS because direct communication between CH and the BS wastes a lot of battery power [5]. In the case of far-flung clusters, choosing the best route for effective multi-hop routing between the CHs is critical. The complexity of selecting the CH and determining the optimal route for CHs to reach BS increases as the network size grows [6]. As a result, the selection of CH and the optimal route for CHs to transmit aggregated raw-data to BS are seen as two separate NP-hard problems in WSN.

Researchers have conducted research using heuristics [7-10] and meta-heuristics techniques to develop energy efficient WSN. However, the work needs to be improved considering CH-selection and routing in WSN. So this motivated us to propose a new technique for CH selection and routing together in this paper. The contributions of this work are:

- Effective CHs are selected using WTSA and a fitness function. Five parameters are used to construct the fitness function: node degree, CH coverage, distance from BS, distance between CHs, and residual energy.
- SN joins the WTSA-selected CHs to form un-equal clusters. Un-equal clusters are created using a cost function which is derived on the basis of CHs residual energy, node degree, distance from BS and intra-cluster distance.
- CHs routing capabilities are intensified with the help of AO. The optimum routes between the CHs and BS are selected using AO and a fitness function.
- The effectiveness of the proposed technique for CH selection and routing is compared against state-of-the-art techniques.

The remaining parts of the paper are organized as follows: literature review of heuristic and meta-heuristic techniques used in WSN are discussed in section 2. Preliminaries regarding the WTSA, AO, network model and energy model are discussed in section 3. Detailed description of the proposed technique WTSA-AO is presented in section 4. The performance and comparison of proposed technique with other state of art techniques are discussed in section 5 and finally Section 6 concludes the paper.

2. Literature survey

Clustered WSNs have a number of issues including CH selection, rising network lifetime, network performance, intra-cluster / inter-cluster communication and routing between CH and BS. Many researchers have attempted to solve these difficulties using heuristic [14] and meta-heuristic techniques [22] from time to time. Researchers who have used heuristic and meta-heuristic techniques in WSN are discussed in this section.

2.1 Heuristic techniques

LEACH was introduced by Heinzelman [1]. LEACH has a number of flaws, including uneven cluster formation and inadequate CH selection. Hybrid energy-efficient distributed clustering approach (HEED) was identified by Yonis [2]. HEED suffered from selection overheads and unbalanced energy consumption. Energy-efficient unequal clustering (EEUC) was proposed by Chengfa [3]. Authors used concept of unequal clustering and inter-cluster routing in EEUC. Gong [4] introduced multihop routing protocol with unequal clustering (MRPUC), its working design is similar to EEUC, but it differs in terms of BS placement and inter-cluster routing trees. Location-based unequal clustering algorithm (LUCA) was developed by Lee [5]. Authors used the concept of shortest possible hop count when relaying data to the BS. Liu [6] presented an energy-balancing unequal clustering approach for gradient-based routing (EBCAG) protocol based on gradient routing. Due to overhead of maintaining gradients EBCAG is considered un-scalable. Constructing optimal clustering architecture (COCA) was proposed by Huan [7]. This protocol is unreliable in due to its complex architecture and recurrent topology creation. Darabkh [8] discovered a balanced power-aware clustering and routing protocol (BPA-CRP). Authors used the concept of batch-based clustering and node death handling. Zhang [9] introduced clustering by fast search and finding of density peaks (CFSFDP). Authors used dynamic threshold to calculate the optimal number of CHs. Adaptive ranking based energy efficient opportunistic routing protocol (AREOR) was proposed by Chithaluru [10]. To transmit data to BS, the authors used a forwarder node.

2.2 Meta-heuristic techniques

A biogeography-based energy saving routing architecture (BERA) was proposed by Lalwani [11]. Authors have presented a biogeography based optimization (BBO) approach for CH selection and routing. Arjunan [12] proposed fuzzy logic based unequal clustering, and ant colony optimization (ACO) based routing (FUCHAR). To choose CHs and bring together un-equal clustering in the network, authors used fuzzy logic technique. Gupta [13] proposed improved cuckoo search and harmony search (iCSHS), the authors used cuckoo search and harmony search algorithm (HSA) for CH selection and routing. Rao [14] created a novel chemical reaction optimization (CRO) based un-equal clustering and routing algorithm (nCRO-UCRA). Authors used CRO to select CHs and to bring inter-cluster routing between CHs. Khabiri [15] developed cuckoo optimization algorithm (COA) based routing protocol (COARP). The authors focused on delaying the first node die in the network to increase the network lifetime. Tianshu [16] invented genetic algorithm (GA) based energy efficient clustering and routing approach (GECR). By using GA, authors improved energy efficiency and load balancing in the network by adding the previous hop's load to the load on each CH. Daneshvar [17] introduced a new technique based on grey wolf optimizer (GWO). Authors used relay approach to prevent energy depletion of remote nodes. Maheshwari [18] employed a butterfly optimization algorithm (BOA) to choose CHs and ACO to build routes from CHs to BS. The performance of the proposed technique was compared by changing the position of the BS. Alazab [19] proposed the fitness averaged rider optimization algorithm (FA-RAO) technique. The authors present an improved technique for CH selection using modified RAO. Sahoo [20] introduced genetic algorithm and particle swarm optimization (GAPSO). Authors used GA for CH selection and PSO for routing. Table 1 summarizes the parameters used in heuristics and meta-heuristic techniques.

According to the literature, routing between CHs in a clustered WSN is an NP-hard problem [21] that can be solved efficiently using meta-heuristic approaches. As shown in Table 1, parameters such as delay, throughput, alive nodes, node coverage, node centrality, and overall energy consumption were given less importance in CH-selection and routing. The complexity of finding CHs and optimized routes between CHs increases as the network grows in size. Previous works [22-23] have

Table 1. Literature survey

Heuristic techniques		
Name of technique	**Parameters used in CH selection**	**Parameters used in routing**
LEACH [1]	Random-PF	MH
HEED [2]	R-ES, ND	MH
EEUC [3]	R-ES, D-CHBS	MH
MRPUC [4]	R-ES, D-CHBS	MH
LUCA [5]	R-ES, D-CHBS	MH
EBCAG [6]	R-ES, D-CHBS	MH-Gradient
COCA [7]	R-ES, D-CHBS	MH
BPA-CRP [8]	R-ES, D-CHBS, ND	MH
CFSFDP [9]	ND, D-CHBS	MH
AREOR [10]	R-ES, D-CHBS	MH-RT
Meta-heuristic techniques		
BERA [11]	BBO:IACD, R-ES, D-CHBS	BBO:ND, R-ES, D-CHBS
FUCHAR [12]	Fuzzy: R-ES, D-CHBS, ND, NC	ACO: D-CH-NH, E-NH
icSHS [13]	Cuckoo Search: R-ES,IACD, ND	HSA: HC, E-NH
nCRO-UCRA [14]	CRO: Average-IACD, D-CHBS	CRO: E-NH, ND-NH, D-NH-BS
COARP [15]	COA:R-ES, IACD, IECD, D-CHBS	Multi-hop: E-NH
GECR [16]	GA: TEC, ARE	GA:D-CH-NH, E-NH
GWO [17]	GWO:R-ES, Pre-EC	TEC, BEC
BOA [18]	BOA: R-ES, IACD, D-CHBS, ND, NC	ACO: R-ES, IECD, ND
FA-RAO [19]	ROA: Delay, R-ES, Ratio IACD, D-CHBS	Multi-hop: D-CH-NH, E-NH
GAPSO [20]	GA: R-ES, D-CHBS, ECR, ARE	PSO: LECH, D-CHBS, CL

Random probability function= Random-PF, Multi-Hop=MH, Node degree= ND, Distance between CH and BS= D-CHBS, Multi-hop based on Gradient= MH-Gradient, Multi-hop based on Routing Table= MH-RT, Node centrality= NC, Residual energy= R-ES, Intra-cluster distance= IACD, Inter-cluster distance= IECD, Energy consumption rate= ECR, Average intra-cluster distance= Average-IACD, Energy efficiency= EE, Predicted energy consumption= Pre-EC, Delay= Delay, Total energy consumption= TEC, Average residual energy= ARE, Hop count= HC, Energy of next hop node= E-NH, Distance between CH and next-hop node= D-CH-NH, Node degree of next-hop node= ND-NH, Distance between next-hop and base station= D-NH-BS, Balancing energy consumption between CHs= BEC, Lowest energy CH= LECH, Cluster length= CL.

simulated a fixed number of SNs in a scenario for CH selection and routing. As a result, there is a need to find optimized routes that help to route data from CHs to BS with minimal delay and maximum throughput under a variety of network scenarios.

3. Preliminaries

This section describes WTSA [28], AO [27], network model and energy model.

3.1 Whale based tunicate swarm algorithm

Singh [28] introduced whale based tunicate swarm algorithm (WTSA). It is a hybrid technique integrating whale optimization algorithm (WOA) [25] and tunicate swarm algorithm (TSA) [26]. The standard equation for updating agent positions in exploration phase of WTSA is given by

$$A(t+1) = A_R(t) - \vec{E}\left|\vec{D}A_R(t) - A(t)\right| \tag{1}$$

where, A is a position vector, t denotes the current iteration, $A_R(t)$ is the position vector selected randomly from the current population, $\vec{E}$, $\vec{D}$ are coefficient vectors used to search the food source and they are calculated using $\vec{E} = 2\hat{u}(\hat{u} - \hat{v})$ and $\vec{D} = 2\hat{v}$ respectively. Here, $\hat{u}$ is a random vector which linearly decreases from 2 to 0 and $\hat{v}$ is also random vector ranges between [0, 1]. The standard equation for obtaining the optimal agent position using exploitation phase of WTSA is given by

$$A(t+1) = \begin{Bmatrix} \vec{P} + \vec{I}\left(\vec{P} - z_1 A(t)\right) & ; z_1 \geq 0.5 \\ \vec{P} - \vec{I}\left(\vec{P} - z_1 A(t)\right) & ; z_1 < 0.5 \end{Bmatrix} \tag{2}$$

where $\vec{P}$ is the optimum position of the food source, z_1 is a random number ranges between [0, 1], $\vec{I}$ is used to prevent positional clash amongst search agents and it is calculated using $\vec{I} = \frac{\widehat{M}}{\widehat{N}}$ where $\widehat{M}$ is a gravity force and it is represented as $\widehat{M} = \widehat{x_2} + \widehat{x_3} - \hat{S}$, $\hat{S}$ is a water flow advection in deep oceans and it is calculated using $\hat{S} = 2.\widehat{x_1}$, $\widehat{N}$ denotes social forces among search agents which is calculated using $\widehat{N} = [Y_{min} + \widehat{x_1}.Y_{max} - Y_{min}]$. Here $\widehat{x_1}, \widehat{x_2}, \widehat{x_3}$ are random variables ranges from [0, 1]. The minimum and maximum speeds for generating social communication are Y_{min} and Y_{max}. The value 1 is allocated to Y_{min} and value 4 is assigned to Y_{max} in this work. Using Eqs. (1) and (2), we get

$$A(t+1) = \begin{Bmatrix} A_R(t) - \vec{E}\left|\vec{D}A_R(t) - A(t)\right| ; if\ (z_2 \times e^{-\frac{t}{\text{Max\_T}}}) > 0.4 \\ \begin{Bmatrix} \vec{P} + \vec{I}\left(\vec{P} - z_1 A(t)\right) & ; z_1 \geq 0.5 \\ \vec{P} - \vec{I}\left(\vec{P} - z_1 A(t)\right) & ; z_1 < 0.5 \end{Bmatrix} ; else \end{Bmatrix} \tag{3}$$

where z_2 denotes random number ranges between [0, 1] and Max_T denotes maximum number of iterations. Positions are updated in WTSA using Eq. (3) and the optimum solution is discovered through a fitness function. If the fitness values of the updated positions are better than those of the prior positions, the updated positions are picked, and the procedure is continued until the maximum number of iterations is not reached.

3.2 Aquila optimizer

AO was introduced by Abualigah [27] as an optimization technique based on the natural hunting behavior of aquila's. To find a near-optimal solution, AO employs four phases: Expanded exploration, narrowed exploration, expanded exploitation, and narrowed exploitation. The problem starts with W, which is a set of candidate solutions generated using Eq. (4)

$$W_{i,j} = RND \times \left(BU_j - BL_j\right) + BL_j, \quad i = 1,2 \dots \dots N \ \& \ j = 1,2,3 \dots D. \tag{4}$$

where RND is a random number between [0, 1], BU_j & BL_j signifies the upper bound and lower bound in a D dimension, N signifies the size of population. To shift from exploration to exploitation AO uses the condition $t \leq \left\{\left(\frac{2}{3}\right) \times \text{Max\_T}\right\}$ where t signifies the current iteration.

Expanded exploration phase: In this phase, aquila uses high soar and vertical stoop to catch the prey. Derivation of this phase is given by Eq. (5)

$$W_1(t+1) = W_{best}(t) \times \left(1 - \frac{t}{Max_T}\right) + \{W_{ME}(t) - W_{best}(t) \times RND\} \tag{5}$$

where, $W_1(t+1)$ denotes the next iteration's solution obtained using the first search method $W_1(t)$. $W_{best}(t)$ is the best attained solution and mean value of solutions acquired at the t^{th} iteration is $W_{ME}(t)$ and it is formulated using $W_{ME}(t) = \frac{1}{N}\sum_{i=1}^{N} W_i(t), \forall \mathrm{j} = 1,2,3 \dots.. \mathrm{D}$

Narrowed exploration phase: In this phase, aquila narrowly explores the target by moving in circles above the target area and then attacks the prey. Derivation of this phase is given by Eq. (6)

$$W_2(t+1) = W_{best}(t) \times Levy(D) + W_R(t) + (p-q) \times RND \quad (6)$$

where $W_2(t+1)$ denotes next iteration's solution achieved through the second search method $W_2(t)$. $W_R(t)$ denotes a random solution from the population selected at t[th] iteration. $Levy(D)$ denotes a levy distribution function. To build the spiral contour above the hunt area p,q are used and they are calculated using $p = r_1 \times \cos(\theta)$ and $q = r_1 \times \sin(\theta)$, where $r_1 = r_2 + 0.00565 \times D_{int}$, $\theta = -0.05 \times D_{int} + \theta_1$ and $\theta_1 = \frac{3\pi}{2}$. Here, D_{int} takes integer values between 1 to D and r_2 is assigned values between 1 and 20.

Expanded exploitation phase: In this phase, aquila plunges quickly towards the target area in a vertical direction with a motive to get close enough to the prey and the attack. Mathematical formulation of this phase is given by Eq. (7).

$$W_3(t+1) = [W_{best}(t) \times W_{ME}(t)] \times \alpha_1 - RND + [(BU - BL) \times RND + BL] \times \alpha_2 \quad (7)$$

Where, $W_3(t+1)$ signifies next iteration's solution achieved through the third search method $W_3(t)$. BU and BL signifies the upper bound and lower bound respectively. α_1, α_2 are exploitation phase adjustment parameters with a fixed value of 0.1 [27].

Narrowed exploitation phase: In this phase, aquila analyzes the movements of prey to reach its near vicinity and then tries to grab and attack them. Derivation of this phase is given by Eq. (8)

$$W_4(t+1) = F_{Qlt} \times W_{best}(t) - (M_1 \times W(t) \times RND) - M_2 \times Levy(D) + RND \times M_1 \quad (8)$$

where, $W_4(t+1)$ signifies next iteration's solution achieved through the fourth search method $W_4(t)$. F_{Qlt} is calculated using $F_{Qlt} = t^{\frac{2 \times RND - 1}{(1-T)^2}}$ and it signifies a quality function that is used to keep the search techniques in dynamic equilibrium. M_1 denotes motion parameter employed by AO in fourth phase to track down the prey and it is calculated using $M_1 = 2 \times RND - 1$, M_2 takes values between 2 to 0, it signifies flight slope values from the first prey location to the last location and it is calculated using $M_2 = 2 \times \left(1 - \frac{t}{\mathrm{Max\_T}}\right)$. The selection probability among the phases expanded & narrowed of exploration and expanded & narrowed of exploitation is same. In all the four phases, the solution of the next iteration found using (5), (6), (7) and (8) is compared with previous solutions based on their fitness values for Max_T times to obtain the best optimal solution.

3.3 Network model

The following network model assumptions are adopted in this study:

- WSN is a network of homogenous r sensor nodes and a fixed base station BS is deployed in a rectangular network of size $Z * Z$ square units.
- Position of r sensor nodes is fixed after their arbitrary deployment in the WSN network and every SN has knowledge about its position coordinates.
- Position of BS is hooked at the centre of the WSN network and by using hello packets BS receives information from SN.

3.4 Energy model

In this study, the proposed energy model by Heinzelman [1] is used to calculate the energy consumption of a SN. Here, Eqs. (9) and (10) are used to determine a sensor node's energy requirements while transmitting and receiving a data packet of size $u - bits$ at a distance $dist$ between source and destination nodes:

$$EGY_{TX}(u, dist) = \begin{cases} u \times EGY_{elec} + u \times \varepsilon_{fs} \times dist^2, dist < dist_{thrs} \\ u \times EGY_{elec} + u \times \varepsilon_{mp} \times dist^4, dist \geq dist_{thrs} \end{cases} \quad (9)$$

$$EGY_{RX}(u, dist) = u \times EGY_{elec} \quad (10)$$

Here, $EGY_{TX}(u, dist)$ and $EGY_{RX}(u, dist)$ are the energy expenditure of transmitter and receiver respectively, EGY_{elec} is the energy dispelled for activating transmitter/receiver circuitry, ε_{fs} and ε_{mp} are amplification energy coefficients for free space and multi-path model respectively. $dist_{thrs}$ is calculated using $dist_{thrs} = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}}$.

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4. Proposed technique WTSA-AO

The working of the proposed technique is divided into three stages of operation in each round. In the first stage BS selects the CHs using WTSA, in the second stage un-equal cluster formation takes place and finally in the last stage routing between the WTSA selected CHs takes place with the help AO. Fig. 1 shows the flowchart of the proposed technique.

4.1 CH Selection using WTSA - Stage 1

To begin stage-1, SNs and BS are deployed in the network region. Following deployment, each SN connects to the BS by delivering a hello packet. The hello packet contains three fields: SN_{id}, $SN_{location}$, and SN_{energy}. After receiving this information from the nodes, BS can begin the WTSA-based CH selection stage-1. WTSA, a hybrid approach presented by Singh [28], is reviewed in section 3.1. Each round of the WTSA-based CH selection mechanism begins with a random selection of initial agents, as described in section 4.1.1. Further, section 4.1.2 explains the fitness function used to determine the ideal position of CHs. Section 4.1.3 explain how WTSA is used to update the CH positions.

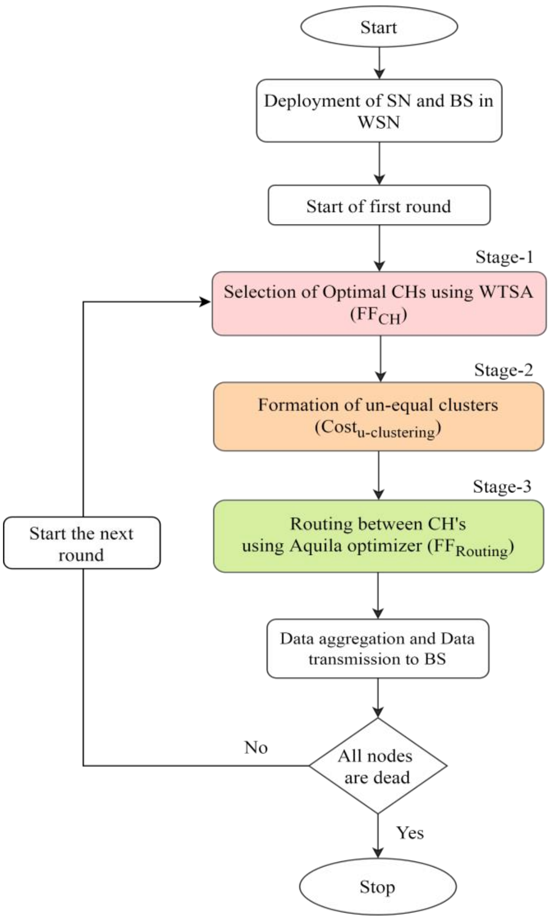


Figure. 1 Flowchart of proposed technique

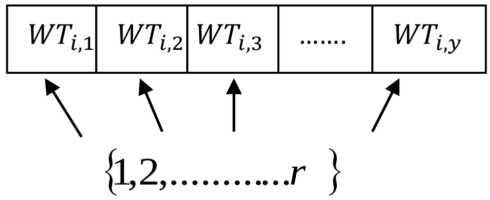


Figure. 2 Solution encoding for CH selection

4.1.1. Initialization and solution encoding

To determine the ideal position of CH in the network, a solution vector is employed to create an initial solution, which is then further processed using WTSA. The solution vector is composed of y nodes (whales/tunicates) chosen at random as CHs from a total of r sensor nodes. The dimensionality dim of each whale/tunicate agent is directly proportional to the number of CHs in the network. Assume that WT_i denotes the i[th] whale/tunicate in the network, and that the position of each whale/tunicate $WT_{i,dim}$ is randomly assigned a node-ID between 1 to r. Solution encoding used for CH selection is illustrated in Fig. 2.

4.1.2. Fitness function for CH selection (FF_{CH})

Fitness function used in the selection of CH is composed of five parameters: node degree, coverage of CH, inter-cluster distance, distance from BS and remaining energy. Derivations of these five parameters are explained below:

a) **Node degree:** P_{ND} signifies a function to calculate the number of nodes attached to a CH. For efficient CH selection, node degree needs to be minimized. Because when a large number of nodes are connected to a CH then it dissipates energy quickly. P_{ND} is calculated using Eq. (11).

$$P_{ND} = \sum_{i=1}^{y} R_i \tag{11}$$

Where, y denotes the number of CHs and R_i denotes the number of nodes attached to CH_i.

b) **Coverage of CH:** P_{IntraD} denotes a function that is used to measure the network coverage of a CH and it is defined as distance between SNs and the CH. For efficient data transmission to the BS, P_{IntraD} needs to be minimized. Because lesser value of P_{IntraD} helps in fast transmission of data from the SNs to CH. Also it also helps in curtailing the overall energy consumption of the CH. Eq. (12) is used to calculate CHs coverage.

$$P_{IntraD} = \sum_{j=1}^{y} \left(\sum_{i=1}^{R_j} \frac{dist(sn_i, CH_j)}{R_j} \right) \quad (12)$$

Where, intra-cluster distance between i^th^ SN and j^th^ CH is measured using $dis(sn_i, CH_j)$ and R_j signifies number of nodes attached to the j^th^ CH.

c) **Distance from BS:** P_{dBS} denotes a function to find the distance between CH and BS. For timely data transmission to BS, P_{dBS} needs to be minimized because CH distance from BS is directly proportional to its energy requirement. So, if CH distance from BS is minimal then the energy requirement to transport data to BS is also minimal. Derivation of this function is given in Eq. (13).

$$P_{dBS} = \sum_{j=1}^{y} dist(CH_j, BS) \quad (13)$$

Where, distance of j^th^ CH from the BS is measured using $dis(CH_j, BS)$ and y denotes the maximum number of CHs.

d) **Distance between CHs:** $InterD$ denotes a function to calculate the inter-cluster distance and it is defined as the distance between two different CHs. For efficient transmission of data, $InterD$ needs to be maximized because CHs selected in close vicinity of each other results in uneven distribution of sensor nodes in their respective clusters. $InterD$ is calculated using Eq. (14).

$$InterD = \sum_{j=1}^{y} \left(\sum_{i=1}^{y} dist(CH_i, CH_j) \right) \quad (14)$$

Where, inter-cluster distance between i^th^ CH and j^th^ CH is measured using $dis(CH_i, CH_j)$. Overall fitness function (FF_{CH}) in this study is realized as a minimization problem, therefore P_{InterD} represents a minimization of $InterD$ and it is calculated using Eq. (15).

$$P_{InterD} = \frac{1}{InterD} \quad (15)$$

e) **Residual energy:** RES denotes a function used to calculate the residual energy. As the CH has to perform the duties of transmitter and receiver, so the cumulative energy requirement of entire CH must be high, it is calculated using Eq. (16).

$$RES = \sum_{i=1}^{y} RE_{CH_i} \quad (16)$$

Where RE_{CH_i} signifies residual energy of i^th^ CH. Overall fitness function (FF_{CH}) in this study is realized as a minimization problem, therefore P_{RE} represents a minimization of RES and it is calculated using Eq. (17).

$$P_{RE} = \frac{1}{RES} \quad (17)$$

All the parameters functions stated in Eqs. (11), (12), (13), (15), and (17) are minimization problems, so the concluding fitness function combining these five parameters is considered as a minimization problem. Final fitness function is calculated using Eq. (18) and is denoted by FF_{CH}

$$\boldsymbol{Minimize} \quad FF_{CH} = \frac{1}{5}\begin{bmatrix} P_{ND} + P_{IntraD} + P_{dBS} \\ +P_{InterD} + P_{RE} \end{bmatrix} \quad (18)$$

4.1.3. Updating WTSA agents

WTSA combines the exploration and exploitation potentials of WOA [25] and TSA [26], to find the best solution. The mathematical formulation of the WTSA [28] technique is already explained in section 3.1. The initial positions of the randomly selected WTSA agents ($\boldsymbol{y}$ nodes) are updated using Eq. (3) and their fitness value is

Algorithm1: CH selection algorithm using WTSA

```
Initialize the parameters and population (WT) for WTSA
While (t <Max_T) do:
        Calculate fitness and update WTbest
        If (z2 × (e^(-t/Max_T)) > 0.4):
                For (i=1:N):
                    //Exploration
                    Update WTnew_i using Eq. (1)
                    Calculate the fitness value of
                    WTnew_i and WT_i using Eq. (18)
                    Update WT_i
                End For
        Else:
                For (i=1:N):
                    //Exploitation
                    Update WTnew_i using Eq. (2)
```

Calculate the fitness value of $WTnew_i$ and WT_i using Eq. (18)
Update WT_i
End For
End If
t=t+1
End While
Return WT_{best}

calculated using Eq. (18).

The fitness value of the updated agents is compared with the initial agents to find the optimal solution. After examining the fitness value of each WTSA agent the best agent in the current round is chosen as a CH. In order to arrive at the optimal solution, the fitness value of the best agent is also compared to the global best solution. The procedure of utilizing Eq. (3) to update the positions of WTSA agents (CH) and Eq. (18) to evaluate the fitness of these agents is repeated until the iteration termination condition is not reached. Algorithm 1 describes the procedure to find the best positions of CHs in the network using WTSA.

4.2 Un-equal cluster formation - Stage 2

Un-equal clusters are built in WTSA-AO to reduce the hotspot problem and to deliver load balancing in the WSN network. The size of un-equal clusters is directly proportional to the distance between WTSA selected CHs and BS. On account of this, CH that is close to the BS forms a tiny cluster, while CH that is far away from the BS forms a larger cluster. To begin stage-2, the BS sends a message to all of the WTSA-selected CHs, telling them to begin publicizing their new role to the remaining SNs in the network. As a result, each WTSA-selected CH broadcasts a network-wide join request to all normal SNs. From all of the requests received, each SN calculates the value of a cost function ($Cost_{u-clustering}$) to join a CH. A node approves the CH join request based on the lowest cost function value. Derivation of cost function is given in Eq. (19).

$$\boldsymbol{Minimize}\ Cost_{u-clustering} = \frac{1}{4}\left[\frac{1}{RE_{CH_j}} + ND_{CH_j} + dist(sn_i, CH_j) + dist(CH_j, BS)\right] \tag{19}$$

Where, RE_{CH_j} denotes the residual energy of j[th] CH, ND_{CH_j} denotes node degree of j[th] CH, distance between i[th] SN and j[th] CH is denoted by $dist(sn_i, CH_j)$, $dist(CH_j, BS)$ denotes distance between j[th] CH and the BS. Value of cost function is lowest for that j[th] CH which has maximal residual energy, minimal node degree, minimal intra-cluster distance and minimal distance from the BS.

4.3 Routing using AO - Stage 3

In a clustered-WSN, appropriate routing between CHs provides energy-efficient data transfer to the BS. Therefore, after establishing un-equal clusters in stage 2, the next step is to start the stage 3, which entails determining the optimum routes for all CHs in the network. This study employs AO, as described in section 3.2, to discover the optimum paths for transmitting raw-data to BS.

4.3.1. Initialization and solution encoding

In AO based routing, each aquila represents a route from every WTSA selected CH to BS and the BS is considered as the prey area. Dimensionality of each aquila is equal to the number of CHs selected by WTSA. The solution vector is initialized in such way that every aquila position in the network represent a next hop (Nhop) towards the BS. Assuming Q_i denotes the i[th] aquila in the network, the position of each Aquila $Q_{i,y}$ is randomly assigned a Nhop from CHs (1 to y). Solution encoding used for routing is illustrated in Fig. 3.

To explain the above concept with the help of an example, a small network with dimensionality 5 (number of CHs = 5) is considered as shown in Fig. 4. We have used a population size of 3 to provide a thorough understanding to the readers, although we used a different population size in actual implementation.

Five CHs are employed in this example and the BS is represented as 6. Every aquila (CH) position is

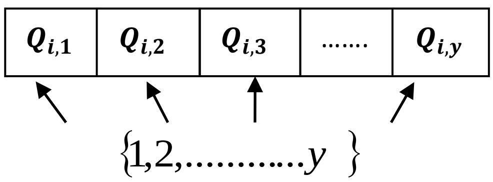


Figure. 3 Solution encoding for routing

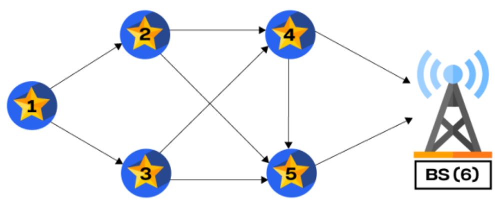
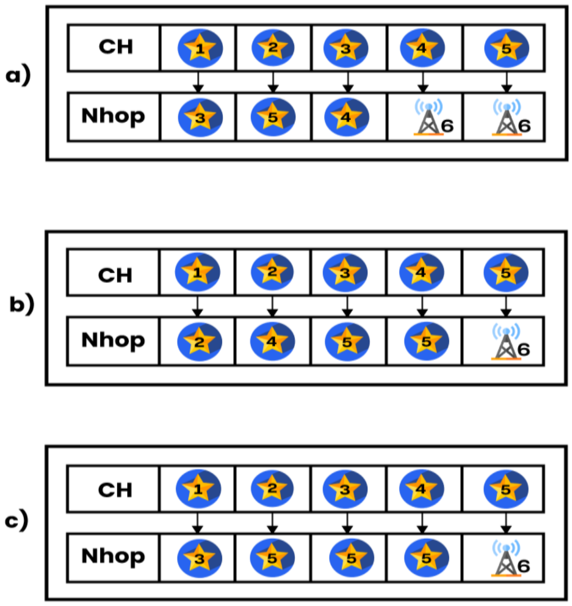


Figure. 4 An illustration of small network



d)

Route-1	
Cluster Head	Route discovery towards BS using Nhop
CH -1	1-3-4-BS
CH -2	2-5-BS
CH -3	3-4-BS
CH -4	4-BS
CH -5	5-BS

e)

Route-2	
Cluster Head	Route discovery towards BS using Nhop
CH -1	1-2-4-5-BS
CH -2	2-4-5-BS
CH -3	3-5-BS
CH -4	4-5-BS
CH -5	5-BS

f)

Route-3	
Cluster Head	Route discovery towards BS using Nhop
CH -1	1-3-5-BS
CH -2	2-5-BS
CH -3	3-5-BS
CH -4	4-5-BS
CH -5	5-BS

Figure. 5 Route discovery for small network

randomly assigned a Nhop from 1 to 5 and three different populations are generated as shown in Fig. 5 (a), (b) and (c). Here, each population lets every CH to discover three different routes towards the BS as shown in Fig. 5 (d), (e) and (f). For instance, CH1 has three routes (Route-1: 1-3-4-BS, Route-2: 1-2-4-5-BS, Route-3: 1-3-5-BS) to reach the BS and CH1 selects the best route out of these three routes with the help fitness function employed by AO.

4.3.2. Fitness function for routing ($FF_{Routing}$)

Three parameters are used in the fitness function to find the optimal route from CH to BS. First parameter calculates the distance between CH and Nhop, second parameter calculates the distance between Nhop and BS and the last parameter calculates the residual energy of Nhop. Derivations of these three parameters are given below.

a) **Distance between CH and Nhop:** P_{dCHNH} denotes a function used to find distance between the CH and its randomly selected Nhop. The derivation of this function is given in Eq. (20).

$$P_{dCHNH} = \sum_{i=1}^{y} dist(CH_i, Nhop(CH_i)) \quad (20)$$

Where, $Nhop(CH_i)$ represents Nhop of i[th] CH.

b) **Distance between Nhop and BS:** P_{dNHBS} denotes a function used to find distance between the randomly selected Nhop and BS. If the distance between Nhop and BS is kept to a minimum, data transfer from CH to BS via Nhop is energy efficient. Derivation of this function is given in Eq. (21).

$$P_{dNHBS} = \sum_{i=1}^{y} dist(Nhop(CH_i), BS) \quad (21)$$

c) **Residual energy of Nhop:** $RESNH$ is a function that is used to calculate next hop's residual energy. Being chosen as Nhop by a CH would be advantageous if Nhop has enough residual energy. Residual energy of Nhop is calculated using Eq. (22).

$$RESNH = \sum_{i=1}^{y} RE_{Nhop(CH_i)} \quad (22)$$

Since the overall fitness function $FF_{Routing}$ is a minimization problem, P_{RESNH} reflects a minimization of $RESNH$ and it is calculated using Eq. (23).

$$P_{RENH} = \frac{1}{RESNH} \quad (23)$$

All parameter functions stated in Eqs. (20), (21), and (23) are minimization problems, so the concluding fitness function combining these is considered as a minimization problem and it is calculated using Eq. (24).

$$\textit{Minimize}$$
$$FF_{Routing} = \frac{1}{2}[P_{dCHNH} + P_{dNHBS} + P_{RENH}] \quad (24)$$

4.3.3. Updating AO agents

As indicated in section 3.2, AO [24] uses four phases to find the optimal solution. In expanded exploration phase Eq. (5) is used to update the positions of AO agents and Eq. (24) is used to compute the fitness. If the updated population's fitness is better than the previous one, it is selected, and the process is continued until the iteration stopping criterion is not achieved. Similarly, in the other three phases of narrowed exploration, expanded exploitation, and narrowed exploitation, Eqs. (6), (7), and (8) are utilized to update the positions. The best fitness value for each phase is used to determine the top candidate positions. After all the iterations in AO, are completed, we get the best optimal route towards the BS. This optimal route allows us to send aggregated data to the BS while conserving energy. Algorithm 2 depicts the AO-based routing mechanism.

Algorithm2: Routing using aquila optimizer

```
Initialize the parameters and population (Q) of AO
While(t<=Max_T) do :
        Calculate fitness and update Q_best
        If (t ≤ ((2/3) × Max_T)) :
                //Exploration
                For (i=1:N):
                    If RND<0.5:
                        //Expanded Exploration
                        Update Qnew_i using Eq. (5)
                    Else:
                        //Narrowed Exploration
                        Update Qnew_i using Eq. (6)
                    End If
                    Calculate the fitness value of
                    Qnew_i and Q_i using Eq.(24)
                    Update Q_i
                End For
        Else:
                //Exploitation
                For (i=1:N):
                    If RND<0.5:
                        //Expanded Exploitation
                        Update Qnew_i using Eq.(7)
                    Else:
                        //Narrowed Exploitation
                        Update Qnew_i using Eq.(8)
                    End If
                    Calculate the fitness value of
                    Qnew_i and Q_i using Eq.(24)
                    Update Q_i
                End For
        End If
        t=t+1
End While
Return Q_best
```

4.4 Summary of WTSA-AO

Fig. 6, is used to summarize the architecture of WTSA-AO. Firstly in stage-1, WTSA is used to select the CHs with the help of FF_{CH} Eq. (18) and then in stage-2 un-equal clusters are built using $Cost_{u-clustering}$ Eq. (19). Finally in stage-3, to determine an energy efficient route from CHs to BS, $FF_{Routing}$ Eq. (24) is used by AO. While transmitting data from CHs to BS, AO assists in finding the best optimal route to reach BS. As a result by using AO, the CHs can transfer data to the BS with maximum throughput and minimal delay.

5. Results and discussion

The experimental setup and results of the proposed technique are discussed in this section. For evaluating the performance of proposed technique, four performance metrics are considered:

- **Number of alive nodes:** The number of alive nodes is defined as the number of nodes that send data to the BS. This metric represents nodes that haven't used up all of their energy yet. This metric is measured in *nodes*.
- **Throughput:** The amount of data packets received by the BS over a given period of time is referred to as throughput, and it is represented by $Throughput = \frac{R_{data}}{T}$, where R_{data} denotes number of data packets received and T denotes simulation time. It is measured in *kbps*.
- **Delay:** Delay is defined as the average time difference between the successfully received data packets by the BS. The difference in time between when a data packet is received by the BS and when a data packet is sent by an SN is

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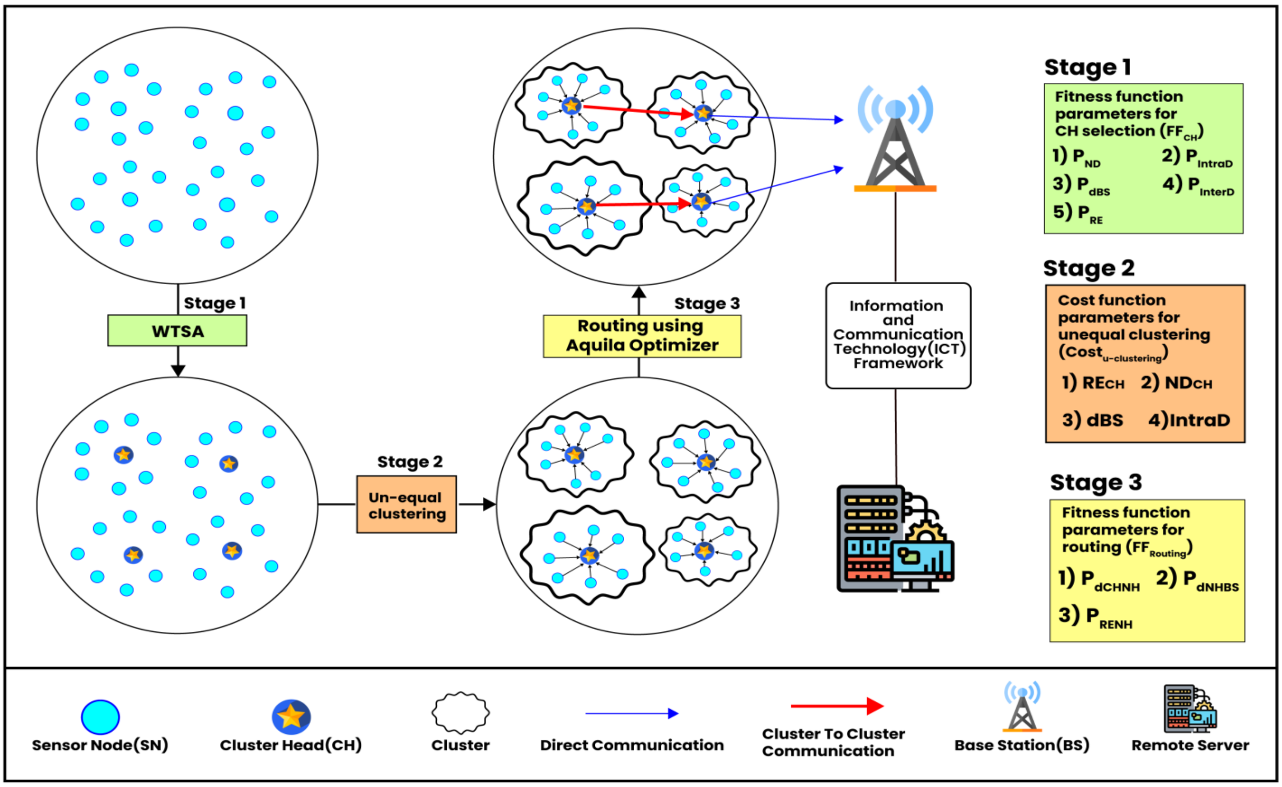

Figure. 6 Architecture of WTSA-AO

Table 2. Simulation parameters

Name of Parameter	Values
Initial energy	0.5 Joules
Free space energy	10×10^{-11} Joules
Transmitted energy	1.5×10^{-7} Joules
Received energy	3.61×10^{-7} Joules
Amplifier energy	1.97×10^{-9} Joules
Energy in data transfer	5×10^{-9} Joules
Size of WSN network	50×50, 100×100, 200×200
Number of nodes	50, 100, 200
Position of BS	Centre of WSN Network
Packet size	4000 bits
Number of rounds	1000
Number of cluster heads	10% of the total nodes
Number of iterations	500

referred to as the time difference. This metric is measured in *seconds*.

- **Average energy consumption:** It is defined as the average amount of energy consumed by each node throughout all rounds of receiving, processing, and transmitting data to the BS. Average energy consumption is calculated by averaging the amount of energy spent by each individual SN per round over the simulation time. This metric is measured in *millijoules*.

5.1 Experimental setup

The proposed technique WTSA-AO is implemented using the MATLAB tool, with Windows 10 (64-bit) Operating system and 8GB of RAM. In the Table 2, the simulation parameters used in the proposed technique are shown.

5.2 Performance analysis

The proposed technique WTSA-AO is compared

with similar state of art techniques BOA [21], WTSA [28], Particle swarm optimization and gravitational search algorithm (PSO-GSA) [24], BERA [14] and LEACH [1]. To evaluate the performance of WTSA-AO we tested for three simulation scenarios: WSN Scenario-1, WSN Scenario-2 and WSN Scenario-3, which were set as: WSN Scenario-1 = (Number of nodes: 50, Area: 50 x 50), WSN Scenario-2 = (Number of nodes: 100, Area: 100 x 100), WSN Scenario-3 = (Number of nodes: 200, Size 200 x 200).

5.2.1. WSN Scenario-1

In this scenario, performance of proposed technique with 50 nodes is shown in following Fig. 7 (a), (b), and (c). Proposed technique has a higher number of alive nodes than the other techniques, as

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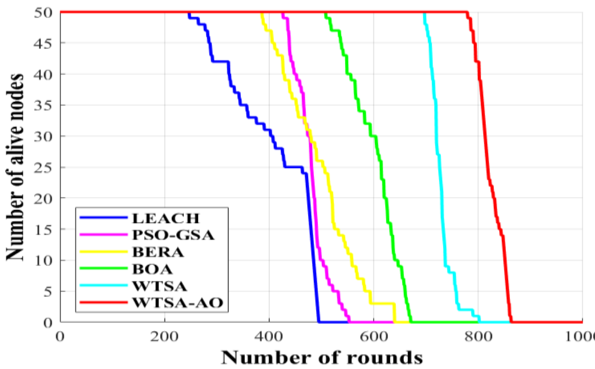
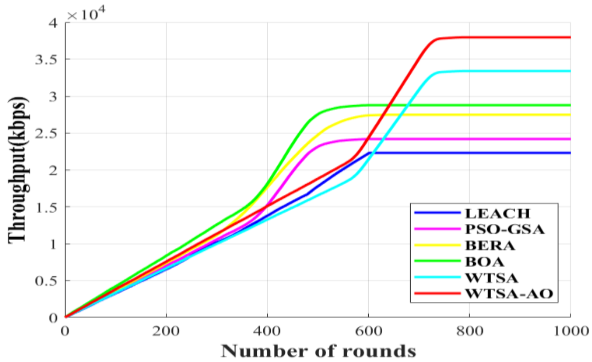
shown in Fig. 7 (a). This is due to the selection of efficient CHs and optimal routes in the proposed technique, which helps to extend the lifetime of nodes by preserving the energy requirement for normal SNs and CHs during transmission of data.

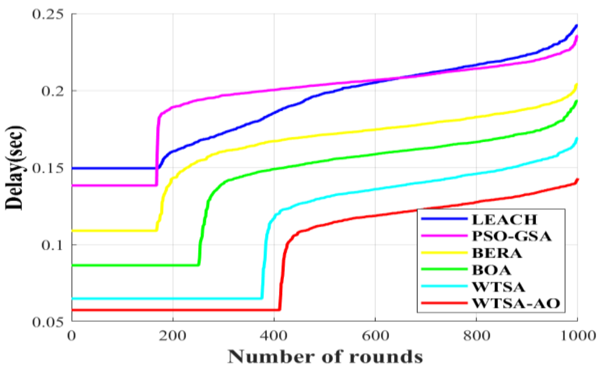
The analysis in terms of throughput as a performance metric is shown in Fig. 7 (b). It is clear from this figure that proposed technique is able to achieve better throughput than the other techniques. This is due to the fact that only those objectives are taken into account in $FF_{Routing}$, which aids in the discovery of the best optimal routes for distant located CHs. The availability of these optimal routes contributes to the overall networks throughput.



(a)



(b)



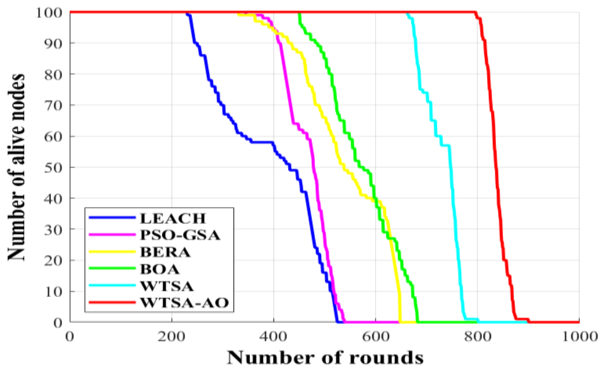
(c)

Figure. 7 Performance analysis for WSN Scenario-1 in terms of: (a) Number of alive nodes, (b) Throughput, and (c) Delay

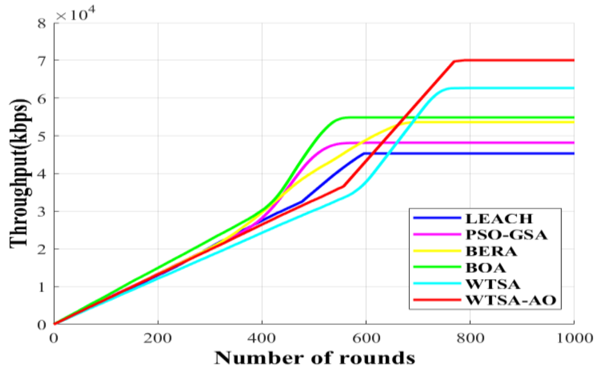
Fig. 7 (c) depicts the analysis in terms of delay as a metric. WTSA-AO when compared to LEACH, PSO-GSA, BERA, BOA and WTSA is able to achieve a minimum delay of 0.141 seconds at the end of the simulation. The dominant cause behind this is the incorporation of Eqs. (13) and (21) in FF_{CH} and $FF_{Routing}$.

5.2.2. WSN Scenario-2

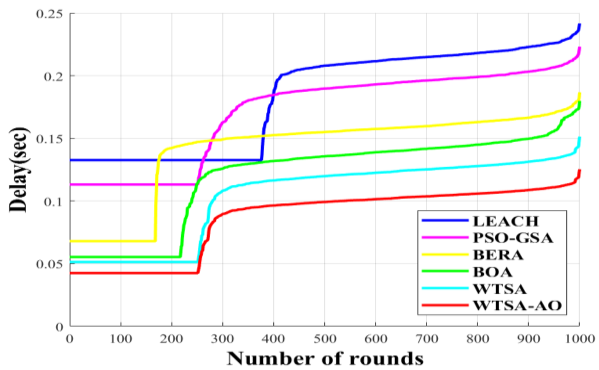
The performance of the proposed technique with 100 nodes in this scenario is shown in Fig. 8 (a), (b), and (c). When the network size and number of nodes are increased, WTSA-AO has large number of alive nodes than other techniques, as shown in Fig. 8 (a).



(a)



(b)



(c)

Figure. 8 Performance analysis for WSN Scenario-2 in terms of: (a) Number of alive nodes, (b) Throughput, and (c) Delay

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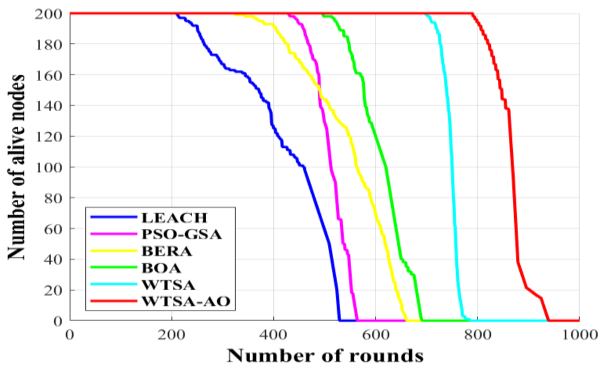
The presence of optimal routes in the network allows for increase in the number of alive nodes. The analysis in terms of throughput for WSN Scenario-2 is depicted in Fig. 8 (b). It is observed that in WSN scenario-2, WTSA-AO outperforms other techniques in terms of throughput. Also in this scenario, the throughput of BERA and BOA is nearly identical, which is an important observation. The increased throughput is primarily due to optimal CH selection using WTSA and the discovery of optimal routes for CHs using AO. Because of the presence of optimized routes, CH transmits more bits to BS. The analysis in terms of delay for WSN. Scenario-2 is depicted in Fig. 8(c). Proposed technique is able to achieve a minimum delay of 0.125 seconds at the end of simulation. The presence of AO-based best-optimized routes for far-flung CHs, allows data to be transmitted quickly and with minimal delay.

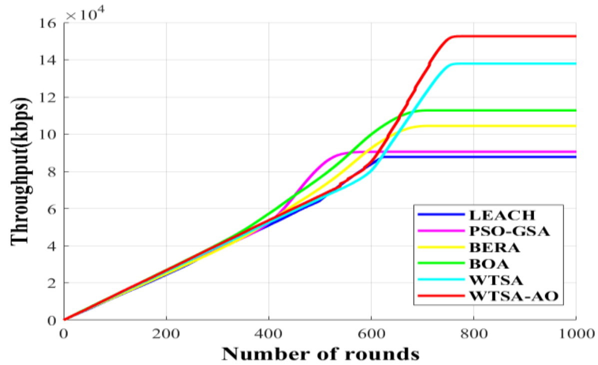
5.2.3. WSN Scenario-3

Fig. 9 (a), (b), and (c) demonstrate the performance of the proposed technique in scenario 3 with 200 nodes. Even when the number of nodes in the network is increased to 200, WTSA-AO is still able to keep the network alive with a higher number of alive nodes as shown in Fig. 9 (a). The justification is that the proposed technique, based on its optimised route selection using AO, prolongs the alive nodes for more number of rounds than rest of the techniques. Also when the number of alive nodes under scenario-3 is compared with other two scenarios, it is depicted that number of alive nodes are more in case of scenario-3 when the network size is changed.

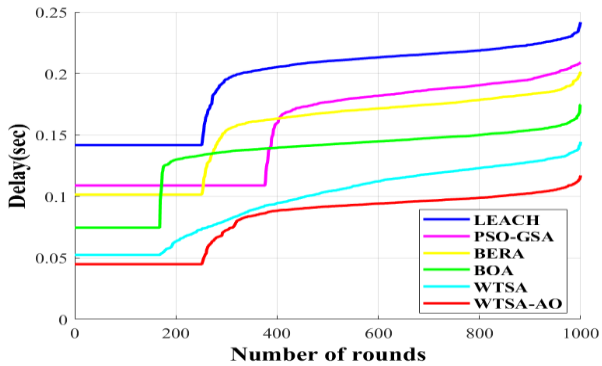
The analysis in terms of throughput for WSN Scenario-3 is depicted in Fig. 9 (b). An important observation in this scenario is that the throughput of PSO-GSA and LEACH is nearly identical. However, the throughput of WTSA-AO is better than other techniques. The achievement of high throughput in WTSA-AO is due to the use of fitness functions FF_{CH} and $FF_{Routing}$, which aid in the selection of best CHs and optimal routes. These fitness functions help to maintain residual energy parameters P_{RE} and P_{RENH} of SN and Nhops respectively. By preserving the residual energy, the number of alive nodes can be kept alive for a longer period of time. As a result, the number of data packets to be transferred to the BS increases.



(a)



(b)



(c)

Figure. 9 Performance analysis for WSN Scenario-3 in terms of: (a) Number of alive nodes, (b) Throughput, and (c) Delay

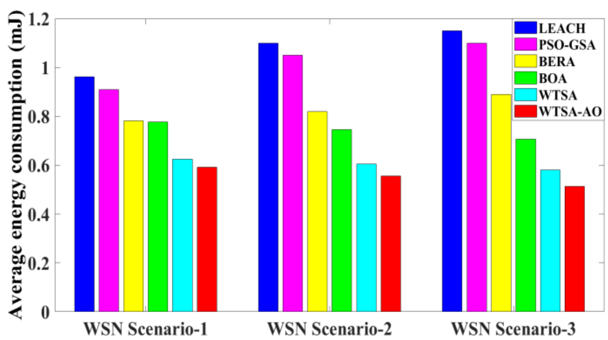


Figure. 10 Comparative analysis in terms of average energy consumption

The performance analysis in terms of delay is depicted in Fig. 9 (c). In this scenario, WTSA-AO is able to achieve a minimum delay of 0.121 seconds at the end of the simulation. Whereas the delay values attained by LEACH, PSO-GSA, BOA, BERA and WTSA at the end of their simulations are 0.241, 0.208, 0.174, 0.201 and 0.154 seconds respectively.

5.3 Comparative analysis of average energy consumption

Fig. 10 shows a scenario-by-scenario comparison of WTSA-AO against other techniques in terms of average energy consumption by every SN per round. When compared with LEACH, the energy consumption of the proposed technique is reduced by 47.77 % on average in all three scenarios. When compared to PSO-GSA, BERA, BOA, and WTSA, the energy consumption of WTSA-AO on an average basis is reduced by 45.11 %, 32.94 %, 25.49 %, and 8.3 % respectively. It is observed that the average energy consumption in the proposed technique is found to be the lowest in all three scenarios. In the proposed technique, with the help of efficient CH selection, the amount of energy required for intra-cluster communication within a cluster is reduced. Also, AO based optimal routes helps to lower down the energy requirement during inter-cluster communication.

6. Conclusion

In this paper, a novel technique for optimized routing in WSN has been proposed. The proposed technique's operation is divided into three stages. The first stage involves CH selection which is optimized considering five parameters: node degree, coverage of CH, distance from BS, inter-cluster distance and residual energy. The second stage involves creating un-equal clusters for the selected CHs by deriving a cost function. The final stage involves finding optimized routes between CHs to transmit data to the BS. Routes between CHs are identified using parameters: residual energy of next hop (Nhop), distance from BS and distance from Nhop. WTSA is used to find the optimal position of CHs by calculating the fitness values using FF_{CH}. To form unequal clusters in the network, SN computes the value of a cost function to join the WTSA-selected CHs. AO is used to find the best optimal routes from distant CHs to BS. To determine the fitness of optimal routes, AO employs $FF_{Routing}$. For evaluating performance of the proposed technique four parameters are considered number of alive nodes, throughput, delay and average energy consumption. The performance of proposed technique is compared with BOA, PSO-GSA, BERA, WTSA, and LEACH under three different network scenarios. The results analysis shows that WTSA-AO is able to achieve a minimum delay of 0.141 seconds for 50 nodes, 0.125 seconds for 100 nodes and 0.121 seconds for 200 nodes. Also the proposed technique is able to reduce the average energy consumption by 25.4 % when compared with BOA and 8.3 % when compared with WTSA. The proposed technique's practical implication is efficient utilization of optimized routes with minimum average energy consumption, minimum delay and high throughput. In the future, the proposed technique can be extended to networks with mobile nodes and multiple BS.

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

The paper background work, methodology, implementation, result analysis and comparison, preparing and editing draft, visualization has been done by the first author. The supervision and review of work has been done by second author.

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