Partical Competitive swarm optimizayion (PCSO) – An optimization enabled routing algorithm for heterogeneous wirelesssensor networks

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Abstract
The evolution of wireless communication, particularly Wireless Sensor Networks (WSNs) are being used extensively in various areas, like military, medical, etc. As an enhancement over WSN in node resources and topology, Heterogeneous WSN (HWSN) is developed. HWSN depends on the heterogeneity of nodal energy.To improve the network lifetime, a routing algorithm, named Particle Competitive Swarm Optimizer (PCSO), is proposed considering several factors, such as predicted residual energy, Link Lifetime (LLT), distance, and delay. PCSO is proposed by the hybridization of Particle Swarm Optimization (PSO) and Competitive Swarm Optimizer (CSO), which is a variant of PSO algorithm. Moreover, the residual energy of the nodes is predicted using Deep Recurrent Neural Network (DRNN) to extend the network's lifespan during routing. The effectiveness of the proposed PCSO-based routing is proven by analyzing its performance. This has been validated by an evaluation of the effectiveness of the proposed methodology in comparison to existing work. using four metrics, namely residual energy, delay, link lifetime and throughput. The experimentation carried out reveals the proposed PCSO-based routing algorithm has better performance with the maximum residual energy of 0.000100285J, minimum delay of 0.21945s, maximum throughput of 58.03571, and maximum LLT of 0.0122sec.

Keywords: Heterogeneous Wireless Sensor Network, routing, Particle Swarm Optimization, Competitive Swarm Optimizer, deep learning

1. Introduction

HWSN is a Wireless Sensor Network (WSN), but with sensor nodes, each having different functionalities. The usage of heterogeneous nodes in proper application can enhance the lifespan of the WSN. In heterogeneous WSN, as the heterogeneous nodes do not require replacement often and contain sustainable energy resource, they can perform complex communication tasks. Moreover, the capacity of heterogeneous nodes in communications and data processing is far greater than those of any common node [12].

1.1 HWSN Routing protocols: In existing techniques, therouting algorithmswere developed to extendthe network performance based on data delivery and latency. The routing paths of the WSNs are mutually isolated, hence each WSN transfer its own gathered information through their own route using sensors.WSNs mainly emphasis on improving energy preservation with negligible overheads during the communication[16][2]. The routing algorithm must be able to adjust to both, resources available and resources required by the nodes. Two fundamental questions must be attended : (i) how to construct a network topology of nodes with diverse resources, varying resource needs and multiple applications; and (ii) how to distribute network traffic while the network is in operation. [17]. Looking at the traditional networking schemes [18][2], the major advantages with the application of WSN are scalability,accuracy, easy deployment, and consistency. As the constraints in WSN are few [19][2], energy utilization is consideredas a rare source and thus, it is significant to involve in improvingthe lifetime and the routing performance of the network. Existing routing approaches are not much feasible for applications used with sensor, because of the changing behavior of sensor nodes. As a result, several researchers [20][2] pave attentionto the development of robust and adaptive routing techniquesto provide energy efficient and optimal route discovery towards the destination [2]. Another concept employed to enhance the route discovery process with energy efficiency for WSNs is hierarchical-based routing techniques [21][2]. Moreover, these approaches are important in the scenarios where scalability is necessary to several sensor nodes with efficient distributed load [2].
This paper proposes a routing algorithm in HWSN with an intention of extending network lifetime.. PCSO is devised newly by the combination of PSO andCSO. The fitness parameters considered in the proposed algorithm are residual energy, distance, delay, and LLT. The contributions made in this research is - Devising a novel optimization algorithm, PCSO, forenhanced routing in HWSN by integrating PSO in CSO with the utilization of fitness factors, like predicted residual energy, distance, delay, and LLT.
The paper is structured as follows: section 2 reviews the existing works; challenges are identified in section-3; section-4 presents the system model; in section 5, the proposed routing algorithm is explained with the architecture; section 6 discusses the results and comparative analysis.

2 Literature Review:

This segment provides an overview of the literature on the subject area pertaining to energy aware routing techniques currently in use in heterogeneous Wireless Network Systems (HWSNs Deepak Sharma, Amol Pbhondekar[1] and others developed Traffic and Energy Alerting (TEAR). This approach took into account the traffic volume of the node, as well as the initial and residual energy of the node. Compared to other algorithms, TEAR demonstrated a higher degree of stability in the multi-heterogeneous scenario. This method achieved effective performance in the presence of traffic heterogeneity, but this method suffers from computational complexity., respectively.Khalid Haseeb., et al. [2] introduced a Reliable Cluster-based Energy-aware Routing (RCER) protocol for increasing the network lifespan, solving computational complexity issue, and also for minimizing the computational cost. In this approach, initially, the network area was partitioned into geographical clusters so that the network can be made energy-efficient. After that, RCER performed routing to improve the performance of next-hop selection usingdifferent factors, such as hop-count, weighted value of Round-Trip Time (RTT), andresidual-energy. This protocol improved the data delivery performance. However, this protocol failed to evaluateits performance on mobile sensors. To solve the issue in [2], SunitiDutt., *et al.* [3] devised a Cluster-head Restricted Energy Efficient Protocol (CREEP) to improve the network lifetime by modifying the cluster head selection thresholds in a two-levelheterogeneous WSN. This technique improved the lifespan of the network, but failed to apply this protocol in more than two level heterogeneity to improve the energy consumption.

Sai Krishna Mothku and RashmiRanjan Rout [4] developed a routing approach using Fuzzy-based delay with the awareness of energy to perform efficient routing in HWSN. Variables, like node's residual energy nodes, standard of the nodal link, availabe buffer, and range were considered as the input parameters to the fuzzy. In addition, the network performance was analyzed using several combinations of input variables. The approach reduced the packet dropping rate, which in turn reduced the delay and the node's energy consumption. However, cost of computation is high in this method.Sanjay K. Malik., *et al* [5] introduced an Enhanced ant-based Quality of Service-aware routing protocol for HWSN (EAQHSeN) where the entire traffic was classified into control traffic and data traffic with less computation cost. Data traffic was further categorized into multimedia traffic and scalar traffic, and the routing decision was taken on the basis of traffic type as well as Quality of Service (QoS) constraints for the traffictype, yielding a performance improvement. This method reduced the delay overhead issues, but the major challenge lies in testing the proposed approach using other Ant Colony Optimization (ACO)-based solutions for the effective performance results.

Sonam Maurya., *et al* [6] devised a Delay aware energy efficient reliable routing (DA-EERR), which is applicable for a large and dense heterogeneous WSNs. The end-to-end latency and energy consumption were balanced using DA-EERR by selecting a hop within minimum distance and energy efficient during data transmission phase. This method achieved the delivery of delay sensitive data on time. However, the challenge lies in utilizing this approach in multiple mobile sink networks in order to yield effective outcomes. Raja Al-Kiyumi., *et al* [7] designed a Distributed Energy-aware Fuzzy Logic- based routing algorithm (DEFL) to address the energy efficiency and balancing problems, simultaneously. This algorithm captured the status of the networkusingsuitable energy metrics and mapped them into its cost values to compute the shortest path. In addition, the fuzzy system was utilized for the mapping operations to include human logic in it. This method significantly improved the energy balancing performance, but this approach increased the communication complexity; thus, degrades the performance of the network. NuraModiShagari., *et al.* [8] developed a method, Energy and traffic aware sleep-awake (ETASA), to prolong energy efficiency and enhanced load balancing in HWSN with improved performance. The method utilized acluster head selection approachto select the nodes with the maximum energy, and less traffic with high number of pairs to provide balanced energy consumption. This mechanism improved the energy efficiency by minimizing the redundant transmission from sensor nodes. However, this technique failed to consider the traffic heterogeneity in different zones that are under a network.

3. Challenges:

The challenges faced by the techniques based on energy aware routing in heterogeneous WSN are as follows,

- TEAR approach was devised for improving the stability period of the heterogeneous WSN. However, This approach did not take into account the concept of multi-heterogeneity, particularly the concept of traffic heterogeneity for real-world WSNs and IoT applications with diverse sensing needs [1].
- A routing mechanism using fuzzy-based delay with energy was devised in [4] for selecting the efficient routes, but the major challenge lies in applying the technique in duty cycle-based network for effective routing performance.
- In [6], DA-EERR was introduced for the densely deployed large heterogeneous WSNs. However, this approach failed to create a power efficient routing using multi mobile sinks for large scale dense network to attain better results.
- DEFL was developed for the lifetime enhancement in heterogeneous WSNs, but the major challenge lies in designing a routing protocol for the delay constrained multi-hop WSN applications to gaintrade-off between the maximization of network lifetime and minimization of end-to-end delay [7].

4. System Model

Assume the network topology [22][7] consisting of 'N' heterogeneous sensor nodes, $V = \{V_1, V_2, \ldots, V_N\}$, deployed in the area '$R$' randomly with dimension '$a \times b$'. Let 'N_S' be the base station located at the center of the area. Each node has a communication range of 'A' and the sensors communicate with the base station using wireless links. The network model of a heterogeneous wireless system is depicted in figure 1. The sensor nodes constitute an initial battery energy, but each node has a different energy level, that is consumed during the transmission and the reception at its radio transceiver. Moreover, the nodes transmit their sensed data to the sink via multiple paths that are created using the proposed PCSO algorithm.

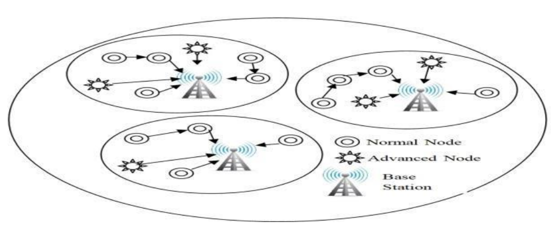


Figure 1. Network model of heterogeneous WSN routing

4.1. LLT calculation

The reliability of a node is defined using the LLT [24] with two nodes p and q, which are in the communication range as,

$$L^T = \frac{-(uv+xy)+\sqrt{(u^2+x^2)t^2-(uy-xv)^2}}{(u^2+x^2)} \tag{7}$$

where, $u = Z_p \cos\theta_p - Z_q \cos\theta_q$, $v = I_p - I_q$, $x = Z_p \sin\theta_p - Z_q \sin\theta_q$, and $y = J_p - J_q$. Here, (I_p, J_p) and (I_q, J_q) are the co-ordinates of nodes p and q; Z_p and Z_q are the mobility speeds of p and q; θ_p and θ_q motion direction of p and q, respectively.

4.2 Mobility

The moving patterns of the nodes and their location, velocity that varies at times are studied in the mobility model [25]. Initially, the position of the nodes p and q is denoted as (I_1, J_1) and (I_2, J_2). The nodes move in direction with angles θ_1 and θ_2 to a distance G_1 and G_2 at time $t = 0 to m$. The Euclidean distance from p to q at $t = 0$ is formulated as,

$$G(pq,0) = \sqrt{|I_1 - I_2|^2 + |J_1 - J_2|^2} \tag{8}$$

Assuming the nodes move with variable velocities c_1 and c_2, the distance travelled by the nodes at t is,

$$G_1 = c_1 \times m \tag{9}$$

$$G_2 = c_2 \times m \tag{10}$$

When $t = m$, the node p moves to a distance G_1 taking a new position $r(I_6, J_6)$, $I_6 = I_1 + c_p \times m \times \cos(\theta)$ (11)

$$J_6 = J_1 + c_p \times m \times \sin(\theta) \tag{12}$$

In a similar way, the node q moves to a distance G_2 taking a new position $k(I_3, J_3)$,

$$I_3 = I_2 + c_q \times m \times \cos(\theta) \quad (13$$

$$J_3 = J_2 + c_q \times m \times \sin(\theta) \tag{14}$$

Thus, the distance between the nodes to new locations $r(I_6, J_6)$ and $k(I_3, J_3)$ at m is,

$$G(rk,m) = \sqrt{|I_6 - I_3|^2 + |J_6 - J_3|^2} \tag{15}$$

5. Proposed optimization-enabled routing in Heterogeneous WSN

This section demonstrates the proposed routing technique in HWSN. Based on the parameters, the routing process is implemented using proposed PCSO algorithm, as explained in the following subsections.

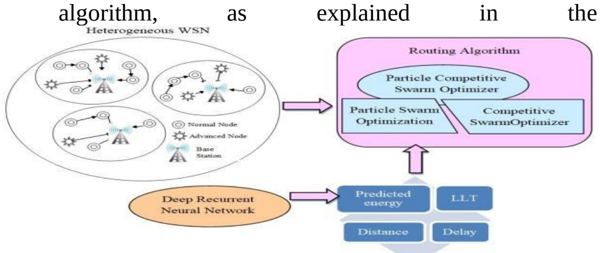


Figure 2. Block diagram of proposed PCSO-based routing

4.1. LLT calculation

Nodes in HWSN are deployed with varying abilities, i.e. each node constitute different computing power and range. HWSNs are usually categorized as i) the network having the nodes deployed with varying communication radius [26] and ii) the network having the nodes deployed with varying energy [27]. The common properties that a heterogeneous routing protocol must satisfy are [28].

(i) Balanced Consumption of Energy: The nodal energies vary, i.e., some nodes are deployed with higher energy than the other nodesin the network so that the former nodes act like hubs where data is collected and sent out., thereby balancing the energy consumption in the HWSN.

(ii) Coordinated Communications: To overcome the obstacles that may happen in the sensing areas, the sensing nodes are deployed with different communication radius[29].

Here, in order to achieve balanced power consumption and to enhance HWSN performance, routing can be done based on the nodes having maximum energy.

5.2. Proposed Particle Competitive Swarm Optimizer with multi-objective functions for routing

This section details the proposed routing algorithm, Particle Competitive Swarm Optimizer, developed for routing in HWSN. The routing algorithm proposed considers various objectives, like predicted energy, delay, distance, and LLT, which are significant for an effective routing. PCSO is the combination of PSO and CSO, which is based on the modification of the former. Hence, the integration of both the algorithms can enhance the effectiveness of proposed algorithm. Proposed PCSO is illustrated in next sub sections with its solution encoding and fitness function.

5.2.1 Proposed Particle Competitive Swarm Optimizer

a) Solution Encoding

This represents the purpose of the PCSO algorithm in a diagrammatic way, as in figure 3. solution vector denotes nodes which can participate in routing procedure. Hence, vector indicates the index of the nodes and the dimension of the solution is the number of nodes that are to be selected, which is notated as Z .

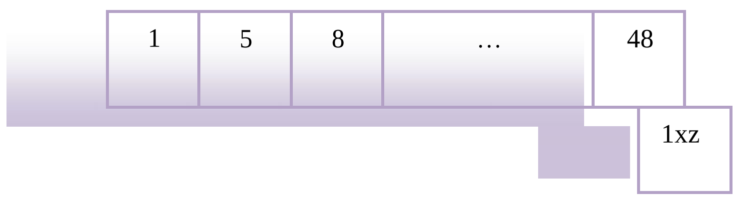


Figure 3. Solution Representation of PCSO-based routing

b) Multi-objective Fitness function

The fitness function defines the parameters that an optimization algorithm is intended for. As the proposed PCSO is developed for HWSN routing, the objectives considered are predicted energy, LLT, distance, and delay. Here, the predicted energy, which is explained in section 5.3, has to be a maximum function to avoid energy depletion in the nodes during the communication. LLT between the nodes must also hold a maximum value, while the distance and delay are reduced. Hence, fitness function is designed as a maximization function, formulated as,

$$\frac{1}{4} \quad E \quad {}^{R}_{p} \qquad \left(S = \qquad {}_{p}\right) + L^{T}_{pq} \Big] \tag{16}$$

where, $P^{E_p^R}$ is predicted residual energy, b_p is delay of p^{th} node, while L^T_{pq} and $G(pq)$ are the LLT and the distance between p and q . Delay is given by ratio of total nodes in route to the total nodes in the network,

Here, f is number of nodes in path i .

d) $b \quad = \frac{i=1}{}$ ***c)*** $\sum V_i$ ***e)*** $_p \qquad N$ (17)

f) Algorithm

However, premature convergence is often a problem when it comes to high-dimensional problems. As a result, variants of PSO had been developed so far to attain a balance between exploration and exploitation phases. Hybridization is one such technique, where we use one of the PSO variants itself, namely CSO.

However, premature convergence is often a problem when it comes to high-dimensional problems. As a result, variants of PSO had been developed so far to attain a balance between exploration and exploitation phases. Hybridization is one such technique, where we use one of the PSO variants itself, namely CSO. Even though CSO was inspired by PSO, it differs from PSO conceptually. In CSO, the particle's personal or global optimum position are not considered in updating phase, but an approach based on pairwise competition was utilized. The update process in CSO depends on the winner, i.e., the lost particle updates its position based on the strategy learnt from the winner [11]. Following steps involved in proposed PCSO algorithm.

1. Initialization:

The first step is the initialization of a swarm, represented as,

$$P(\kappa) = \{P_1(\kappa), P_2(\kappa), \ldots, P_F(\kappa)\} \tag{18}$$

where, F is size of swarm and κ is iteration count. Every particle in the swarm indicates a candidate solution and a velocity vector having 'h' dimension as,

$$X_j(\kappa) = \{x_{j,1}(\kappa), x_{j,2}(\kappa), \ldots, x_{j,h}(\kappa)\} \tag{19}$$

$$W_j(\kappa) = \{w_{j,1}(\kappa), w_{j,2}(\kappa), \ldots, w_{j,h}(\kappa)\} \tag{20}$$

The particles are assigned into $F/2$ couples and they are involved in a competition, at each iteration. The particle that has the best fitness at the end is known as the winner and it is added to the next generation of the swarm $P(\kappa+1)$. Meanwhile, the particle that failed in the competition is the loser, who update the position on the basis of winner's position as well as velocity. Loser is also be passed to $P(\kappa+1)$. Thus, all the particles are allowed to the compete at least once and the position and velocity of $F/2$ particles are updated.

2. Fitness computation:

After the initialization, the fitness of the particles is computed using equation (16) to find the winner and the loser at each iteration.

3. Update process:

Completing the R^{th} competition, the loser's position will be updated based on its velocity, which depends on the winner's position as,

$$X_R^l(\kappa+1) = X_R^l(\kappa) + W_R^l(\kappa+1) \tag{21}$$

$$W^l(\kappa+1) = Z_1(R,\kappa)W_R^l(\kappa) + Z_2(R,\kappa)\left(X_R^w(\kappa) - X_R^l(\kappa)\right) + \lambda Z_3(R,\kappa)\left(\bar{X}_R(\kappa) - X_R^l(\kappa)\right) \tag{22}$$

where, $W_R^l(\kappa)$, and $X_R^l(\kappa)$ are the velocity and position of the loser in R^{th} round at iteration κ. $X_R^w(\kappa)$ denotes the position of the winner in R^{th} round at iteration κ, $Z_1(R,\kappa)$, $Z_2(R,\kappa)$ are randomly generated numbers in [0,1], $\bar{X}_R(\kappa)$ is the mean location value of particles, and λ is parameter controlling mean value.

Substituting equation (22) in equation (21),

$$X_R^l(\kappa+1) = X_R^l(\kappa) + Z_1(R,\kappa)W_R^l(\kappa) + Z_2(R,\kappa)\left(X_R^w(\kappa) - X_R^l(\kappa)\right) + \lambda Z_3(R,\kappa)\left(\bar{X}_R(\kappa) - X_R^l(\kappa)\right) \tag{23}$$

$$X_R^l(\kappa+1) = X_R^l(\kappa) + Z_1(R,\kappa)W_R^l(\kappa) + Z_2(R,\kappa)X_R^w(\kappa) - Z_2(R,\kappa)X_R^l(\kappa) + \lambda Z_3(R,\kappa)\bar{X}_R(\kappa) - \lambda Z_3(R,\kappa)X_R^l(\kappa) \tag{24}$$

$$X_R^l(\kappa+1) = X_R^l(\kappa)[1 - Z_2(R,\kappa) - \lambda Z_3(R,\kappa)] + Z_1(R,\kappa)W_R^l(\kappa) + Z_2(R,\kappa)X_R^w(\kappa) + \lambda Z_3(R,\kappa)\bar{X}_R(\kappa) \tag{25}$$

To hybridize PSO with CSO, the search efficiency and the simplicity of PSO are the major criteria. PSO also comprises a particle swarm, each containing a position and velocity, indicating a candidate solution. Velocity and location update in PSO are given based on the terms in CSO by,

$$W_R^l(\kappa+1) = \alpha W_R^l(\kappa) + \beta_1 o_1(\kappa)\left(U^l(\kappa) - X_R^l(\kappa)\right) + \beta_2 o_2(\kappa)\left(V(\kappa) - X_R^l(\kappa)\right) \tag{26}$$

$$X_R^l(\kappa+1) = X_R^l(\kappa) + W_R^l(\kappa+1) \tag{27}$$

where, α is the weight of inertia, β_1 and β_2 are the acceleration coefficients, $o_1(\kappa)$ and $o_2(\kappa)$ are the random vectors in [0,1], $U^l(\kappa)$ is the personal best solution, while $V(\kappa)$ is the global best.

Substituting equation (26) in equation (27),

$$X_R^l(\kappa+1) = X_R^l(\kappa) + \alpha W_R^l(\kappa) + \beta_1 o_1(\kappa)\left(U^l(\kappa) - X_R^l(\kappa)\right) + \beta_2 o_2(\kappa)\left(V(\kappa) - X_R^l(\kappa)\right) \tag{28}$$

$$X_R^l(\kappa+1) = X_R^l(\kappa)[1-\beta_1 o_1(\kappa) - \beta_2 o_2(\kappa)] + \alpha W_R^l(\kappa) + \beta_1 o_1(\kappa) U^l(\kappa) + \beta_2 o_2(\kappa) V(\kappa) \tag{29}$$

$$X_R^l(\kappa)[1-\beta_1 o_1(\kappa) - \beta_2 o_2(\kappa)] = X_R^l(\kappa+1) - \alpha W_R^l(\kappa) - \beta_1 o_1(\kappa) U^l(\kappa) - \beta_2 o_2(\kappa) V(\kappa) \tag{30}$$

$$X_R^l(\kappa) = \frac{X_R^l(\kappa+1) - \alpha W_R^l(\kappa) - \beta_1 o_1(\kappa) U^l(\kappa) - \beta_2 o_2(\kappa) V(\kappa)}{[1-\beta_1 o_1(\kappa) - \beta_2 o_2(\kappa)]} \tag{31}$$

Substituting the above equation in equation (25),

$$X_R^l(\kappa+1) = \frac{X_R^l(\kappa+1) - \alpha W_R^l(\kappa) - \beta_1 o_1(\kappa) U^l(\kappa) - \beta_2 o_2(\kappa) V(\kappa)}{[1-\beta_1 o_1(\kappa) - \beta_2 o_2(\kappa)]}[1-Z_2(R,\kappa) - \lambda Z_3(R,\kappa)] + Z_1(R,\kappa) W_R^l(\kappa) + Z_2(R,\kappa) X_R^w(\kappa) + \lambda Z_3(R,\kappa)\overline{X}_R(\kappa) \tag{32}$$

$$X_R^l(\kappa+1) - \frac{X_R^l(\kappa+1)}{[1-\beta_1 o_1(\kappa) - \beta_2 o_2(\kappa)]}[1-Z_2(R,\kappa) - \lambda Z_3(R,\kappa)] = Z_1(R,\kappa) W_R^l(\kappa) + Z_2(R,\kappa) X_R^w(\kappa) + \lambda Z_3(R,\kappa)\overline{X}_R(\kappa) - \frac{\alpha W_R^l(\kappa) + \beta_1 o_1(\kappa) U^l(\kappa) + \beta_2 o_2(\kappa) V(\kappa)}{[1-\beta_1 o_1(\kappa) - \beta_2 o_2(\kappa)]}[1-Z_2(R,\kappa) - \lambda Z_3(R,\kappa)] \tag{33}$$

$$\frac{X_R^l(\kappa+1)[1-\beta_1 o_1(\kappa) - \beta_2 o_2(\kappa) - 1 + Z_2(R,\kappa) + \lambda Z_3(R,\kappa)]}{[1-\beta_1 o_1(\kappa) - \beta_2 o_2(\kappa)]} = Z_1(R,\kappa) W_R^l(\kappa) + Z_2(R,\kappa) X_R^w(\kappa) + \lambda Z_3(R,\kappa)\overline{X}_R(\kappa) - \frac{\alpha W_R^l(\kappa) + \beta_1 o_1(\kappa) U^l(\kappa) + \beta_2 o_2(\kappa) V(\kappa)}{[1-\beta_1 o_1(\kappa) - \beta_2 o_2(\kappa)]}[1-Z_2(R,\kappa) - \lambda Z_3(R,\kappa)] \tag{34}$$

$$\frac{X_R^l(\kappa+1)[Z_2(R,\kappa) + \lambda Z_3(R,\kappa) - \beta_1 o_1(\kappa) - \beta_2 o_2(\kappa)]}{[1-\beta_1 o_1(\kappa) - \beta_2 o_2(\kappa)]} = Z_1(R,\kappa) W_R^l(\kappa) + Z_2(R,\kappa) X_R^w(\kappa) + \lambda Z_3(R,\kappa)\overline{X}_R(\kappa) - \frac{\alpha W_R^l(\kappa) + \beta_1 o_1(\kappa) U^l(\kappa) + \beta_2 o_2(\kappa) V(\kappa)}{[1-\beta_1 o_1(\kappa) - \beta_2 o_2(\kappa)]}[1-Z_2(R,\kappa) - \lambda Z_3(R,\kappa)] \tag{35}$$

$$X_R^l(\kappa+1) = \frac{[1-\beta_1 o_1(\kappa) - \beta_2 o_2(\kappa)]}{[Z_2(R,\kappa) + \lambda Z_3(R,\kappa) - \beta_1 o_1(\kappa) - \beta_2 o_2(\kappa)]}\left\{ Z_1(R,\kappa) W_R^l(\kappa) + Z_2(R,\kappa) X_R^w(\kappa) + \lambda Z_3(R,\kappa)\overline{X}_R(\kappa) - \frac{\alpha W_R^l(\kappa) + \beta_1 o_1(\kappa) U^l(\kappa) + \beta_2 o_2(\kappa) V(\kappa)}{[1-\beta_1 o_1(\kappa) - \beta_2 o_2(\kappa)]}[1-Z_2(R,\kappa) - \lambda Z_3(R,\kappa)] \right\} \tag{36}$$

This forms the update equation of the proposed PCSO algorithm.

4. Finding the winner and the loser:

Once the solution is updated, include the updated solution to $P(\kappa+1)$ and find the better solution.

5. Termination:

Step 2-4 are repeated until the completion condition is met.
The pseudocode of the algorithm mentioned above is presented below.

Pseudocode of Proposed PCSO algorithm:

	Begin
	Initialize the population randomly
	For $\kappa=\max(S)$ **do**
	Compute the fitness of all the particles in $P(\kappa)$ using equation (16)
	Choose $X_R^1(\kappa)$ and $X_R^2(\kappa)$ randomly from the particles
	If $S(X_R^1(\kappa))\le S(X_R^2(\kappa))$
	$X_R^w(\kappa)=X_R^1(\kappa)$, $X_R^l(\kappa)=X_R^2(\kappa)$
	Else
	$X_R^w(\kappa)=X_R^2(\kappa)$, $X_R^l(\kappa)=X_R^1(\kappa)$
	endif
	Include $X_R^w(\kappa)$ in $P(\kappa+1)$
	Update $X_R^l(\kappa+1)$ using equation (36)
	Include $X_R^l(\kappa+1)$ **in** $P(\kappa+1)$
	End for
	$\kappa=\kappa+1$
	Terminate

6. Results and Discussion

The findings obtained by implementing the PCSO routing algorithm in the HWSN are discussed in the next subsection.

6.1 Simulation Setup

MATLAB was used to implement the suggested work. and simulation in a PC with intel core i3 processor, 4 GB RAM, and OS 10. The simulation is conducted in 3 setups, by setting network of 100, 150, and 200 nodes for the analysis. The simulation table and its parameters are illustrated in table 1.

Table 1. Simulation setup

Simulation parameters	**Values**
Field dimension (x)	100
Field dimension (y)	100
Transmission energy	$50*10^{-8}$
Receiver energy	$50*10^{-8}$
Energy in free space	$10*10^{-11}$
Amplifier energy	$0.0013*10^{-11}$

6.2 Evaluation metrics

The metrics employed to evaluate the performance of the proposed PCSO-based routing are residual energy, delay, Link lifetime and throughput. The residual energy, Link lifetime and delay of nodes in HWSN are computed using equations (6), (7) and (17). The throughput is defined as,

$$H^T=\frac{n_l}{n^T} \tag{41}$$

where, n_l is the number of packets transferred from a source node to the destination at a time, n^T is the total number of packets.

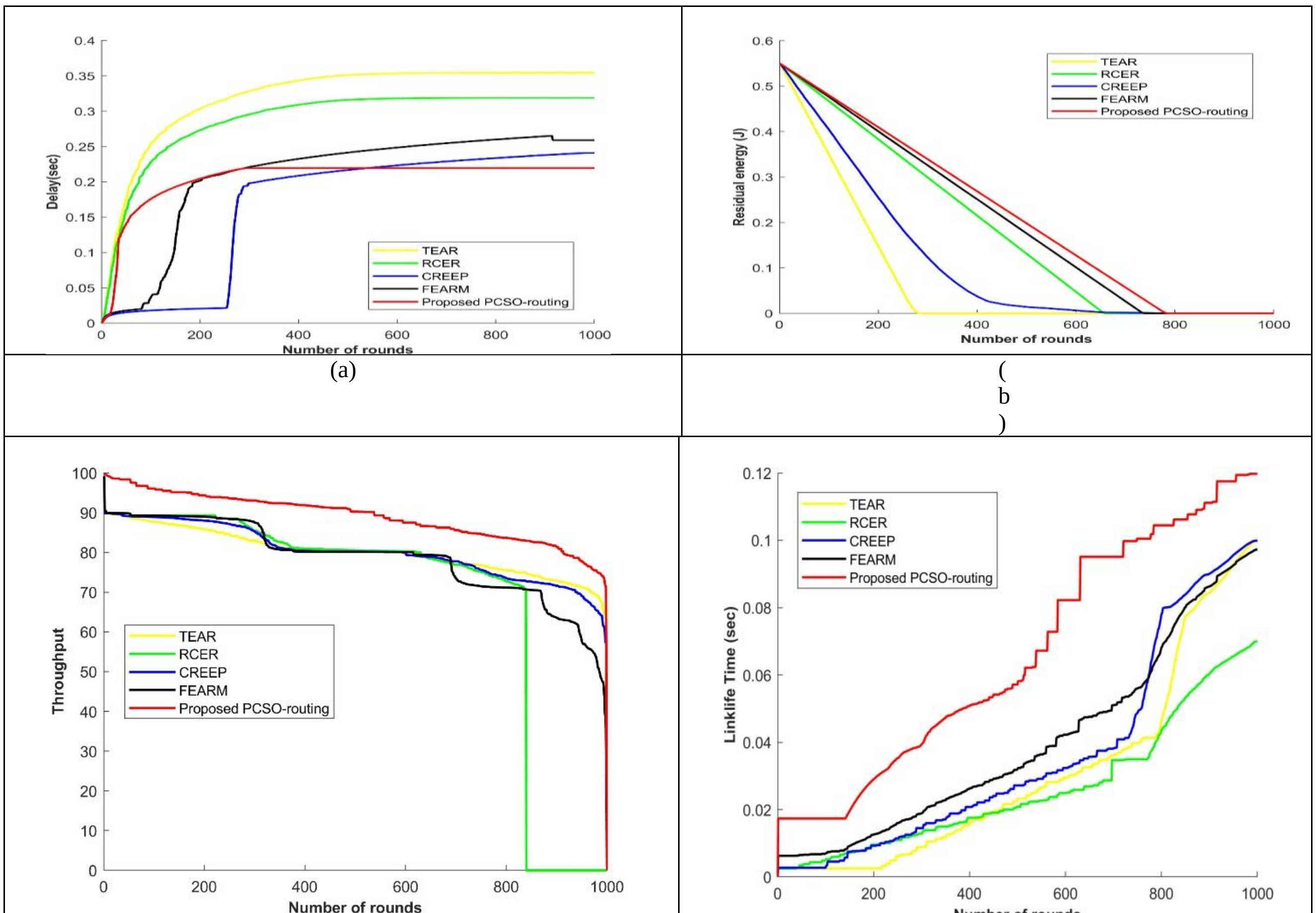
6.3 Comparative methods

The methods considered for analysis for comparison of the results of proposed method are i) TEAR [1], which utilizes the traffic, and energy to enhance the network stability, ii) RCER [2] that expands network lifetime by a clustering approach, considering remaining energy, hop count and RTT, iii) CREEP [3], which is also aimed to improve the LLT of the network, iv) Fuzzy-based Energy-Aware Routing Mechanism (FEARM) [4], which was developed to increase the network performance, with the utilization of buffer, residual energy, quality of nodal links, as well as distance.

6.4Comparative Analysis:

i) For N=100

Figure 5 shows the results of the comparative techniques using three metrics for N=100. Figure 5.a, presents the analysis based on delay for the number of rounds varied from 1 to 1000. Initially, all the techniques have zero delay, which becomes 0.00425 sec (s), 0.00382 s, 0.00134 s, 0.00225 s, and 0.00092 s for TEAR, RCER, CREEP, FEARM, and PCSO-based routing, when the number of rounds is 2. Even though the delay is the minimum for CREEP till 538thround, it starts to increase over the number of rounds. When the number of rounds is 539, the delay attained is 0.35227s, 0.31704s, 0.21947s, 0.24445s, and 0.21945s, by TEAR, RCER, CREEP, FEARM, and PCSO-based routing. Finally, the delay attained by the existing methods, TEAR, RCER, CREEP, and FEARM, is 0.35441s, 0.31897s, 0.24091s, and 0.25891s, while that in the proposed PCSO-based routing is 0.21945sfor the round 1000. In figure 5.b, the analysis based on residual energy is shown, where the initial energy for all the techniques is 0.55 Joules (J), which then reduces when the number of rounds is increased. As shown in the graph, when the number of rounds is 500, the residual energy in TEAR, RCER, CREEP, FEARM, and PCSO-based routing is 0, 0.13121 J, 0.01419 J, 0.17602 J, 0.19809 J. As the number of rounds reach 786, all the existing techniques exhaust the energy, while the proposed technique has a residual energy of 1.88E-06 J. The analysis based on throughput is presented in figure 5.c, The proposed method has a throughput of 90.2778, while the existing TEAR, RCER, CREEP, and FEARM have only a throughput of 80.4, 80.5556, 80.19231, and 80.12196. The analysis based on Link lifetime is presented in figure 5.d. The proposed method has a Link lifetime of 0.119sec, while the existing TEAR, RCER, CREEP, and FEARM have only a Link lifetime of 0.099sec, 0.0699sec, 0.099sec, and 0.097sec respectively at 1000th round. Thus, it is obvious that the proposed method has better results than the existing techniques.

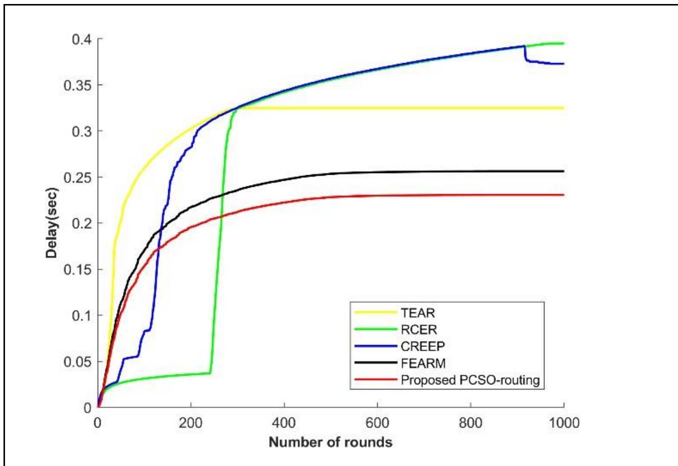


(a) (b) (c) (d)

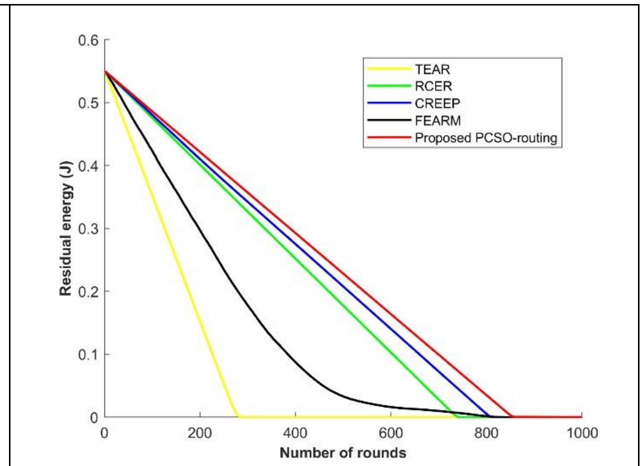
Figure 5. Analysis using N=100 a) delay b) residual energy c) throughput d) LLT

ii) For N=150

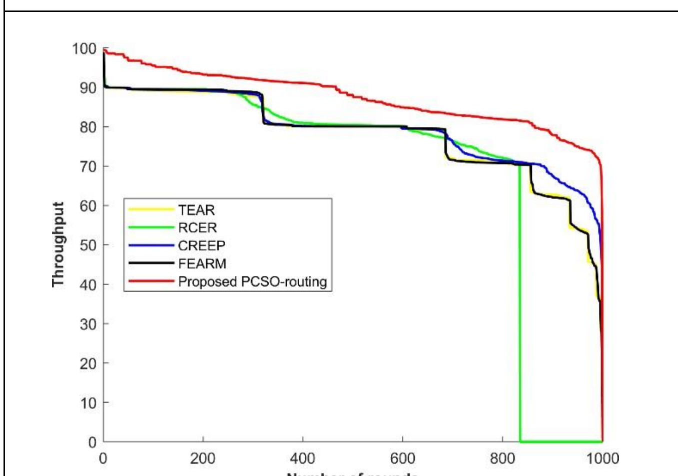
The comparative analysis results for N=150 is given in figure-6. In figure-6a, analysis based on delay for comparative techniques is picturized where RCER has the minimum delay initially, i.e., upto the round 265 with the value 0.20049s. Meanwhile TEAR, CREEP, FEARM, and PCSO-based routing has the delay of 0.31949s, 0.31724s, 0.23004s, 0.20704s. From then on the proposed PCSO-based routing shows the least delay among the existing techniques. When the number of rounds is 1000, the delay attained by TEAR, RCER, CREEP, FEARM, and PCSO-based routing is 0.3248s, 0.3949s, 0.37296s, 0.25629s, 0.23067s. The analysis based on residual energy for N=150 is presented in figure 6.b, where the proposed method has the residual energy till the 1000th round. The amount of energy remaining in the suggested PCSO-based route is 0.0001J, while the existing methods have 0J. Figure 6.c shows the results of throughput, wherein 94.83871, 94.58333, 95.38462, 98.88889, 99.5856 is the initial throughput achieved by TEAR, RCER, CREEP, FEARM, and PCSO-based routing. When these techniques reach 1000th round the throughput values are 19.5, 0, 43.22581, 19.15888, 58.03571, respectively; Figure 6.d shows the results of Link lifetime, wherein 0.00262sec, 0.0052sec, 0.0126sec, 0.0029sec, and 0.0175sec is the initial Link lifetime achieved by TEAR, RCER, CREEP, FEARM, and PCSO-based routing. When these techniques reach 1000th round the Link life time values are 0.099sec, 0.113sec, 0.073sec, 0.099sec, and 0.120sec respectively; thereby showing the proposed method has the maximum performance.



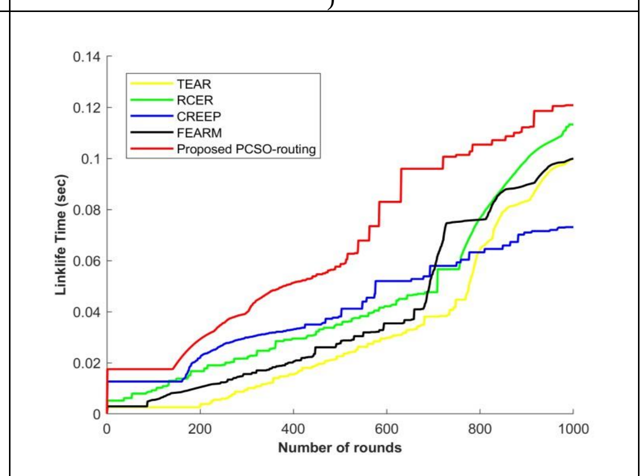
(a)



(b)



(c)

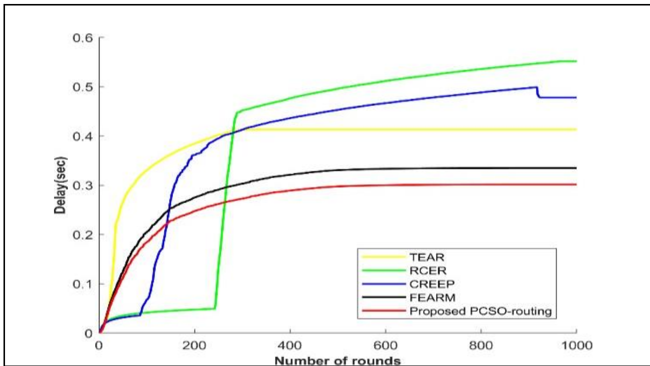


(d)

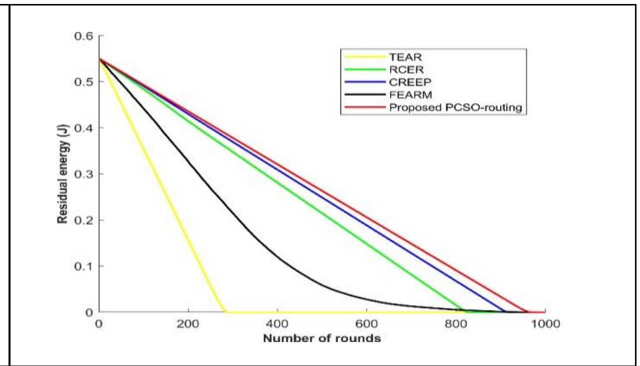
Figure 6. Analysis with N=150, a) delay b) residual energy c) throughput d) LLT

iii) For N=200

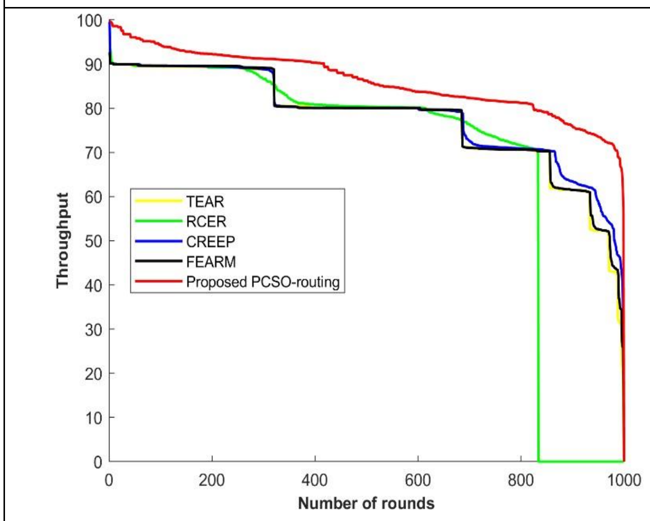
In figure 7, the results of comparative analysis for HWSN with N=200 is presented, where figure 7.a is delay and figure 7.b and figure 7.c are residual energy and throughput. The delay value increases from an initial value of 0 to the maximum for all the techniques at the final round. However, the proposed PCSO-based routing has the minimum delay of 0.3017s, while TEAR, RCER, CREEP, and FEARM have the delay of 0.4134s, 0.55192s, 0.47831s, and 0.33522s. The analysis based on energy shows that comparing the existing techniques, proposed method have the residual energy till round 970, with the value 3.65E-07J, except CREEP. However, till the round 967, the proposed method have maximum residual energy of 0.000169111J, while CREEP has a value of 9.02E-05J, and the other existing techniques with 0 energy remaining. Moreover, the throughput analysis depicts that the maximum throughput attained by proposed method is 56.86275 at 999th round, while that in TEAR, RCER, CREEP, and FEARM is 10, 0, 30.42553, and 16.47723. The Link lifetime analysis depicts that the maximum Link lifetime attained is by the proposed method is 0.1226sec at 999th round, while that in TEAR, RCER, CREEP, and FEARM is 0.104sec, 0.104sec, 0.094sec, and 0.099sec. Hence, it is clear that the proposed PCSO-based routing has attained the minimum delay, and maximum throughput, except the residual energy in this scenario.



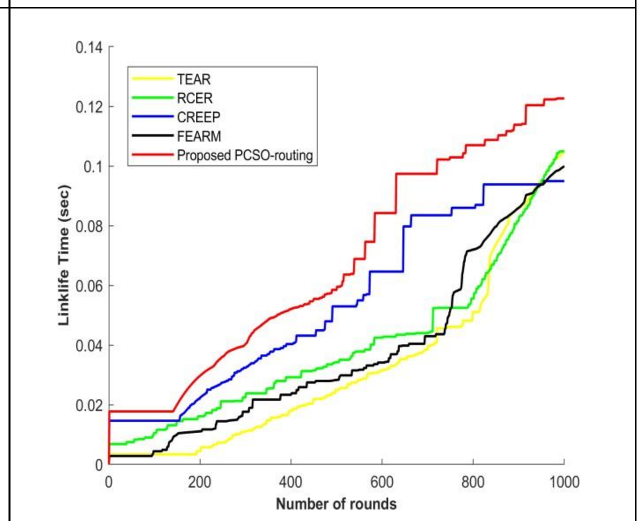
(a)



(b)



(c)



(d)

Figure 7. Analysis with N=200 a) delay b) residual energy c) throughput d) LLT

6.5 Discussion

Table 2 shows the comparative analysis of results attained by proposed PCSO-routing with that of the existing techniques for N=100, 150, and 200. As shown in the table, the proposed routing technique has the minimum delay, maximum residual energy and throughput, and maximum Link lifetime. Among the three setups, the minimum delay attained by the proposed method is when N=100 with the value of 0.21945s, while TEAR, RCER, CREEP and FEARM has the value 0.32482s when N=150, 0.31897s when N=100, 0.24091s when N=100, and 0.25629s when N=150, respectively. The maximum residual energy of the proposed PCSO-routing has till the maximum round than that of the existing methods is 0.000100285 J, when N=150. Even though FEARM has better residual energy than the proposed method it has been depleted within least number of rounds when compared with the proposed. Analyzing the throughput, it is observed that proposed method has increased throughput of 58.03571 when N=150 at maximum number of rounds. Meanwhile, RCER has ‘0’ throughput; CREEP and FEARM had a throughput of 56.5 and 24.27184 for N=100. The maximum Link lifetime achieved by the proposed PCSO-routing at N=200 is 0.122 sec. The existing method such as TEAR, RCER, CREEP, FEARM achieved LLT of 0.104 sec, 0.104sec, 0.09sec, 0.09sec respectively. Although the proposed PCSO-routing has slightly lower performance in terms of residual energy and throughput for N=100, the maximum performance has been gained than that of the existing approaches when N=150 and N=200.

Table 2. Result discussion on comparative techniques

Metrics		**Methods**				
		TEAR	**RCER**	**CREEP**	**FEARM**	**Proposed PCSO-routing**
N=100	***Delay (s)***	0.35441	0.31897	0.24091	0.25891	**0.21945**
	Residual energy (J)	$1.04x10^{-7}$	$8.83x10^{-9}$	$1.42x10^{-5}$	$5.18x10^{-6}$	$1.88x10^{-6}$
	Throughput	**57.5**	0	56.5	24.27184	56.86275
	Link Lifetime(sec)	0.0999	0.0699	0.0999	0.0972	0.1197
N=150	***Delay***	0.32482	0.3949	0.37296	0.25629	**0.23067**
	Residual energy	3.04E-08	5.55E-07	5.32E-07	5.28E-06	**0.000100285**

	Throughput	19.5	0	43.22581	19.15888	58.03571
	Link Lifetime(sec)	0.0999	0.1132	0.0730	0.0999	0.120
N=200	***Delay***	0.41345	0.55191	0.47831	0.33522	**0.3017**
	Residual energy (J)	3.87x10-9	4.88x10-7	2.65x10-6	5.42x10-6	3.65x10-7
	Throughput	10	0	30.42553	16.47727	56.86275
	Link Lifetime (sec)	0.1049	0.1049	0.0949	0.0999	0.1226

7. Conclusion:

The present paper explains PCSO, a novel optimization algorithm, which is designed by integrating PSO and CSO, for effective routing in HWSN. The proposed algorithm extends the network lifetime with the utilization of fitness parameters, like predicted residual energy, LLT, delay and distance. Predicting the residual energy makes the network efficient as nodes with maximum power can be determined beforehand so that the nodes that may drain out soon is not involved in the routing process. For the prediction of residual energy, DRNN can be used and updated to the network so that the only the nodes that hold the energy to the maximum time extent or simulation time are selected by the proposed PCSO algorithm. Finally, the performance of the proposed PCSO-based routing is evaluated and compared with existing works, namely TEAR, CREEP, RCER, and FEARM, using residual energy, delay and throughput. The results show that the proposed routing method has the highest residual energy of 0.000100285J, minimum delay of 0.21945s, maximum throughput of 58.03571, and maximum LLT of 0.122sec respectively. In future, security can be considered as an important factor to secure the network information and the algorithm can be utilized in several applications, like health-care, agriculture, etc.

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