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SSE Path Routing protocol for WSN IOT Using Fuzzy Mean Weighted Code and Enthalpy ANN-GOA

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Abstract:

Wireless Sensor Networks (WSNs) play a key role in the Internet of Things (IoT) by delivering cost-effective solutions for specific IoT applications. The amount of energy used to transport data from a sensor node to its destination is a significant consideration when developing wireless sensor network routing strategies. A variety of routing protocols are utilised in WSN to improve network performance. When a node's mode transitions from active to sleep, the efficiency declines because data packets must wait at the starting point where they were transmitted, which increases packets' waiting time and end-to-end latency, resulting in an increase in energy consumption. This study proposes the SSE Path routing protocol as a Scalable, Secure, and Energy Efficient Routing Protocol for WSN IoT. Our proposed protocol, first selecting the nodes using a single-hop clustering algorithm. Second, FMWC (Fuzzy Mean Weighted Code) based packet coded operation for the security of packet. Finally, Scalable Enthalpy Artificial Neural-Network Based Grasshopper Optimization Algorithm (EANN-GOA) algorithm for selecting the congestion-free path for transit the data packets. The experimental results revelations the dominance of presented protocol comparing with the existing protocols.

Keywords: Wireless Sensor Network, cluster, packet code, ANN, GOA.

1. INTRODUCTION

Because of recent scientific developments in the fields of microelectronics, sensing machines, and wireless communication systems, wireless sensor networks have attracted worldwide attention (WSNs). WSNs are made up of a variety of low-power devices called motes or sensor nodes. They connect with one another via wireless media and carry out a variety of functions, such as environmental monitoring and battlefield observation, among others. The sensor nodes, on the other hand, face a variety of obstacles, including limited transmission diversity, processing capacity, garage capacity, and power resources [1]. WSNs are made up of a large number of battery-powered sensor nodes that convert observed data into electrical signals for subsequent processing. The WSN has no infrastructure, and the sensors are dispersed haphazardly [2]. The WSN's job is to collect data from the network on a regular basis and deliver it to the base station, which then decides what to do next. WSN is crucial in many WSN-assisted IoT applications.[3].

Clustering enables multi-hop transmission, data aggregation, compression, and the removal of redundant data. The benefits of clustering are dependent on the precision of the clustering set of rules and the health of the parameters being used. Unlike distributed clustering algorithms, which employ local information from individual sensor nodes, centralised clustering algorithms provided by the BS provide the most reliable clustering solutions since the WSN's overall view is available [5]. One of the most difficult components of clustering is determining the quality of the clusters. A range of criteria, such as density and separation, can be used to assess cluster quality (inter-cluster and intra-cluster distances). The data in each

cluster should be close enough together to avoid overlap, and the clusters formed should be unique enough to avoid overlap. The three metrics used to calculate separation are the distance between the closest data in two clusters, the distance between the farthest data in two clusters, and the distance between the centres of two clusters [6].

When it comes to cluster routing, LEACH has been used as a benchmark in the majority of cases. Indeed, LEACH aids in the encapsulation of an energy balancing data-forwarding technique that strives to achieve energy balance. As a result, LEACH has gained widespread adoption due to a goal to extend network longevity while conserving sensor node energy [7-8].

Clustering is a powerful hierarchical routing-based strategy that splits the network into distinct zones of nodes with similar capabilities, allowing the network to scale more easily. Clustering is a technique for increasing the capacity of a machine by grouping together similar types of sensors. All of the nodes are thought to have similar potential and skills. A node can have a variety of roles assigned to it, including CH, gateway, and cluster member. A CH is a cluster organiser that facilitates communication within the cluster; on the other hand, a gateway sensor connects sensor signals across clusters and communication ranges [9]. Routing performance is harmed by frequent CH selection because nodes are preoccupied on node selection rather than communication. The elements that influence cluster formation and CH communication are still being researched [10-11]. By utilising data aggregation techniques at CHs, the clustering methodology minimises the bulk of acquired data by maintaining only significant information [12].

CH selection is extremely important in cluster-based routing methods. Most clustering algorithms focus solely on CH selection and cluster formation [13], rather than data routing after cluster creation. Data about data compactness and separateness can be obtained from clustering outcomes. Furthermore, a large number of clusters can duplicate data on data distributions, which are almost certainly unique from class distributions. Furthermore, the data cannot be analysed based on classification results. As a result, the mixture with clustering outcomes might provide varied but supplemental data for classifications, reducing the uncertainty associated with classification outcomes due to a lack of comprehension or inadequate data [15].

The suggested methodology's key contribution is that it uses the SSE Path routing protocol to pick a congestion-free path for data packet transit from source to destination.

- The clustering technique employs a criterion based on four variables at the next-hop node.
- Protect data packets that are encoded using a fuzzy mean weighted code.
- The Scalable Enthalpy Artificial Neural-Network Based Grasshopper Optimization Algorithm (EANN-GOA) algorithm selects the least congested channel for data packet transmission.

The remainder of the paper is divided into sections as follows: section 2 discusses a review of related work and the issue description, and section 3 describes the SSE path routing protocol in WSN. Then, in part 4, the experimental analyses are described in depth, and lastly, in section 5, the conclusion is explained.

2. RELATED WORKS

Sukhwinder Sharma et.al [16] delivered the Due to actually appropriate absorption of excess energy by advanced nodes, simulation-based overall performance evaluation of the suggested method in comparison to several relevant strategies reveals that HEC produces a longer solid region, higher throughput, and larger electricity dissipation. The stability length development is around 65 percent, 30 percent, 15 percent, and 17 percent for LEACH, SEP, FAIR, and HEC-based SEP protocols, respectively. The scalability of the suggested technique is further investigated using various sector lengths and sensor node counts.

Phet Aimtongkhamet.al [17] delivered the basic To deal with traffic congestion induced by temporary events, a congestion management approach was developed. Congestion, on the other hand, is typically caused by a series of anomalies and, as a result, might last for a long period. As a result of this research, a congestion manipulation approach that can handle any sort of congestion has been developed. In three primary areas, the analysis followed a vague set of criteria for addressing traffic congestion: optimal path selection, traffic rate modification using a momentum indicator, and optimal timeout placement for a circuit breaker to prevent continuing congestion.

Muhammad Muzzammil et.al [18] presented the fundamental ideas and concepts of magnetic field communication by defining the major blocks, outlining the issues with each block, and emphasising new advancements The three key blocks that must be recognised are: 1) transmit and acquire coils, 2) matching network, and 3) magnetic field channel characteristics. The first block demonstrates how a single-dimensional coil is utilised to construct a directional communication link between a transmitter and receiver, followed by multi-dimensional and meta-material coils to overcome the directionality problem. The matching network further highlights the distinctions between induction and resonance phenomena, as well as their implications for variety and capacity. The 0.33 block mentions the elements that affect magnetic fields, which are important for underwater wireless communication with magnetic fields. Finally, the research looks at current advancements at the physical, MAC, and network layers.

Quan Wang et.al [19] Firstly, The lemmas for the link between any adjacent layers, the ideal cluster length, and the optimal Cluster Head (CH) distribution, as well as their proofs, were proposed. Furthermore, the 3rd function of Backup Cluster Head (BCH) was described, as well as the accompanying mechanism for rotating jobs among the CH and BCH, to alleviate the "Hot Spot Problem" and reduce energy consumption caused by the rotation of CH functions. The protocols for Energy-Efficient Compressive Sensing-based Clustering Routing (EECSR) are then described in detail. Finally, thorough modelling tests were carried out in order to determine its energy efficiency.

Thangaramya et.al [20] presented the intelligent routing in WSNs for IoT is a significant phenomenon that must be addressed if the network's Quality of Service is to be improved (QoS). Additionally, avoiding severe packet loss or packet drop, quick energy depletion, and network unfairness, which results to a reduction in node overall performance and growth input off for packet delivery, the energy required for communication inside IoT-based sensor networks is an important task. As a result, there may be a significant desire to evaluate energy utilisation by utilising nodes to improve overall network performance using software that employs intelligent device learning techniques for making powerful routing decisions.

Poonam Rani et.al [25] provides a linear electronic communication technique that may be scaled up or down according to the application's requirements. The simulation findings show that scaling the network by adding/removing nodes in the same network region has no effect on the network's lifespan, but that if the network's size is increased/decreased, the network's lifetime is improved as well.

Rani Poonam et.al [26] presented a routing scheme is proposed which is predicated on forming a Minimum Spanning Tree (MST) and works on basis of flat based routing technique

to perfectly utilise vitality and improves the era of the system together with minimising the transmission delay. Transmission between the clusters via Cluster Heads (CH's) has been suggested obsessed on the gap of separation among sensors. Here forms a linear chain among the nodes and connect them in such a fashion that reduces overall cost of the governing system.

Rani Poonam et.al [27] Wireless Sensor Network (WSN) consists of a network with huge quantity of sensors that are deployed to accomplish a selected task. These low cost sensors are proficient of aggregating and communicating the sensed information over the sphere.. However, these nodes being powered by battery are energy constrained. Proposes a routing protocol supported cluster formation among same style of sensor nodes (SN) for gathering of knowledge at intermediate nodes within the cluster and these intermediate nodes further transmits data to resource opulence sink.Many procedures are already to be had withinside the literature on energy-efficient routing for WSN's.

- The existing routing approach reduces the problem of broadcast storm in clustered sensor networks, but it also increases energy consumption and reduces transmission security.
- A scalable and energy-efficient routing system converts long-distance communication into tiny multi-hop distance communication with load balancing, resulting in a lower and more consistent Stability Factor (SF) problem.

3. PROPOSED SYSTEM

The deployment strategies, as well as the routing protocol, determine the efficacy of WSN in IoT, particularly large-scale applications. When a network is distributed over a vast area, the performance of WSN-assisted IoT suffers. This piece is a demonstration. SSE Path routing protocol for WSN IoT is a scalable, secure, and energy efficient routing mechanism. Because several sources attempt to deliver their packets to a destination at the same time, which is a common scenario in IoT applications, this protocol is designed to work in networks with high traffic.Our suggested protocol initially employs a criterion that is a function of four factors: residual energy, distance to the sink, node density, and network average energy at the next-hop node in order to pick nodes using a clustering technique. Second, a packet coded procedure based on FMWC (Fuzzy Mean Weighted Code) to ensure packet security. Finally, the Scalable Enthalpy Artificial Neural-Network Based Grasshopper Optimization Algorithm (EANN-GOA) algorithm is used to choose the least congested channel for data packet transmission. The proposed technique is depicted in figure 1 as a block diagram.

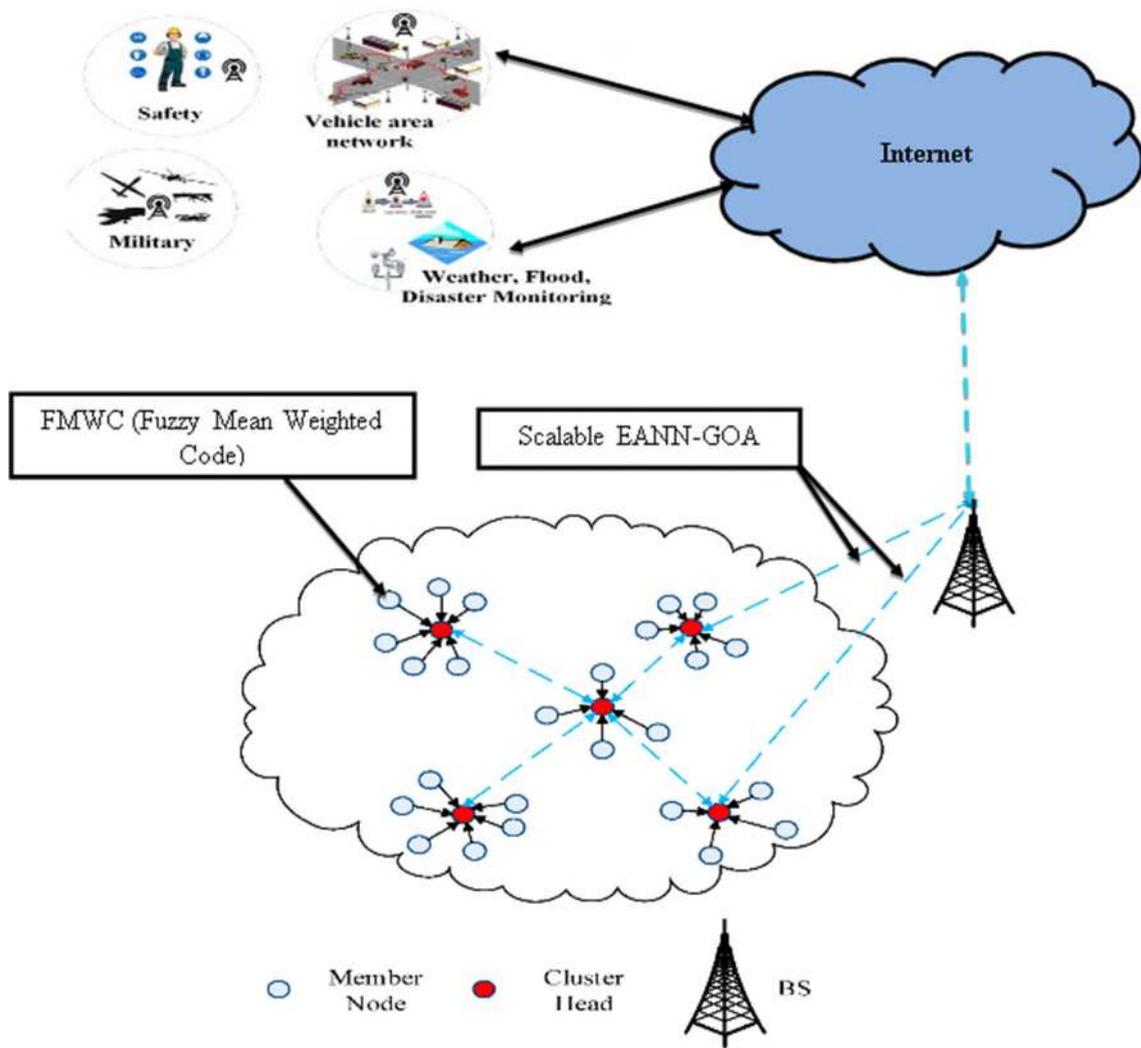


Figure 1: Proposed technique

3.1 Selecting node using One-hop Clustering

A WSNs produced of nodes from a few hundred or even thousand, where each node is associated to each other sensors. Clustering is a key approach for extending the network period in wireless sensor networks. The routing protocol is a method of determining the best path for data to take from source to destination. The data packets are clustered using the single-hop clustering technique in this case. Single-hop communication occurs in very small sensor networks where the base station and data packets are so close that they can interact directly with one other. Now we'll look at the four factors: Residual Energy, Distance to Sink, Node Density, and Network Average Energy at the next-hop node. The one-hop clustering is represented as follows: Let $CN = \{g_i; i = 1, 2, \dots, n\}$ be cluster nodes, n be several clusters, $CH = \{c_i; i = 1, 2, \dots, n\}$ be initial centroids, the clustering of the nodes of WSN is shown in figure 2.

3.1.1 Residual Energy:

The energy model depicts the energy level of the network. The node's energy level at the start of the simulation is the initial value of the energy model defined in the node. After routing packets have been received or delivered, the residual energy is the current value of energy in a node.

$$RE_x = C_x * \frac{E_{residual}}{E_{max}} \quad (1)$$

Where C_x is the initial percentage of cluster heads among all 'n' nodes, $E_{residual}$ is represents current residual energy, E_{max} presents maximum energy.

3.1.2 Distance to the sink:

Different distances from the sink generate an imbalance in energy depletion. Based on the distance to the sink and the routing scheme, divide the entire network into a few groups. Each group has a cluster number and a node that belongs to it.

$$Ds_x = C * \frac{D_j}{\sum_{j=1}^n D_j} (1 \leq j \leq n) \quad (2)$$

Here, D_j is the distance to the sink and lower index means near to the sink, C represents a cluster in each group.

3.1.3 Node density

The node density N_{den} implies the relation tightness among the activity nodes. All nodes would know the number of their neighbors which is called node density. To avoid network congestion, node density can be evaluated and a threshold value for sub-cluster formation can be determined.

$$N_{den} = \sum_{i=1}^n \left(\frac{C_x}{n} \right) \quad (3)$$

Whereas N_{den} represents node density, n denotes the number of nodes, C_x presents cluster in each group.

3.1.4 Network Average Energy:

The cluster heads are selected using a probability formula based on the ratio of each node's residual energy to the average energy of the network.

$$E_a = \frac{\sum_{i=1}^n E_{residual}}{n} \quad (4)$$

Where E_a Presents average energy

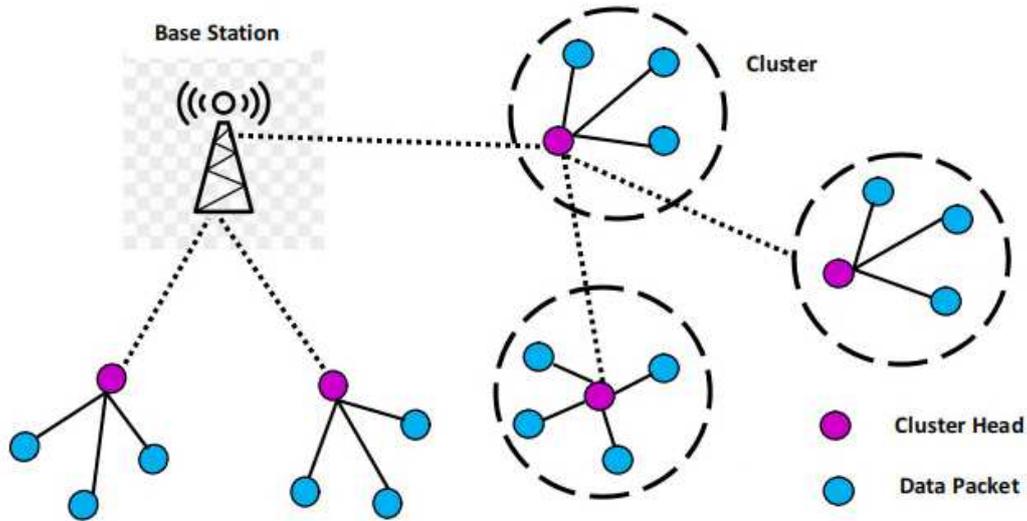


Figure 2: Single-hop clustering Algorithm

3.2 Packet Coding Method

The objective of our proposed work is to accomplish a superior usage of the transfer speed and to decrease the network congestion in the multimedia media information dispersal situation. To do as such, the network coding procedure is utilized to decrease the amount of times a message has been retransmitted. The source is placed at opposite ends of a comparable street and offers N hop's space of interest in our proposed study, as shown in Figure 1. Source disseminates non-security information among the vehicles in the common part of the road between them.

Instead of relay broadcasting, our proposed approach uses entropy-based path selection for information transfer and encodes it into a single packet before rebroadcasting it in the network, and in this manner lessens the transfer speed utilization just as postponement at the relay. The relay is thought to have the option to advance the packets and play out an FMWC procedure on the got packets before rebroadcasting them. It is additionally expected that the transfer is mindful of the normal information rates that the source is sending.

3.3.1 Operational example of TPC

A basic network topology is explored, with four stations, each of which is within transmission range of the others. A source node (sn_1) sends a data packet (Pk) to a destination node (sn_k), which is also sending a packet (dk) to the source station. Furthermore, this special bidirectional communication is supported by two helper or relay nodes (R_1 and R_2). Pursues is a word that describes the entire procedure.

Direct 1: At direct T_1 , the source node sn_1 transfers the data packet Pk to the destination node n_2 .

Direct 2: At direct T_2 , destination node sn_2 desertsions to demodulate the info packet, so propagation a packet request (PKR) packet requesting for the cooperation of the neighboring relay nodes along with the data packet B' , destined to the source node sn_1 .

Direct 3: The receiving of PKR at direct T_3 starts the nodes $R_1 R_2$ and to become started relays and check the trust-based optimized set up their link to participate in the dispute contention phase.

Direct 4: At direct T_4 , the setup link R_1 terminates and R_1 transfers the coded packet Pk , dk to the nodes $sn_1 sn_k$ and concurrently.

Direct 5: At direct T_5 , the destination node sn_k retrieves the original packet Pk and sends back an acknowledgment (AKE) packet subsequently it can decipher legitimately the Adaptive quantum logic-based coded packet.

Direct 6: At direct T_6 , the source node sn_1 acknowledges the packet dk since it can decode appropriately the coded packet Pk , dk the network topology operation with transmitting packet coding is depicted in figure 2.

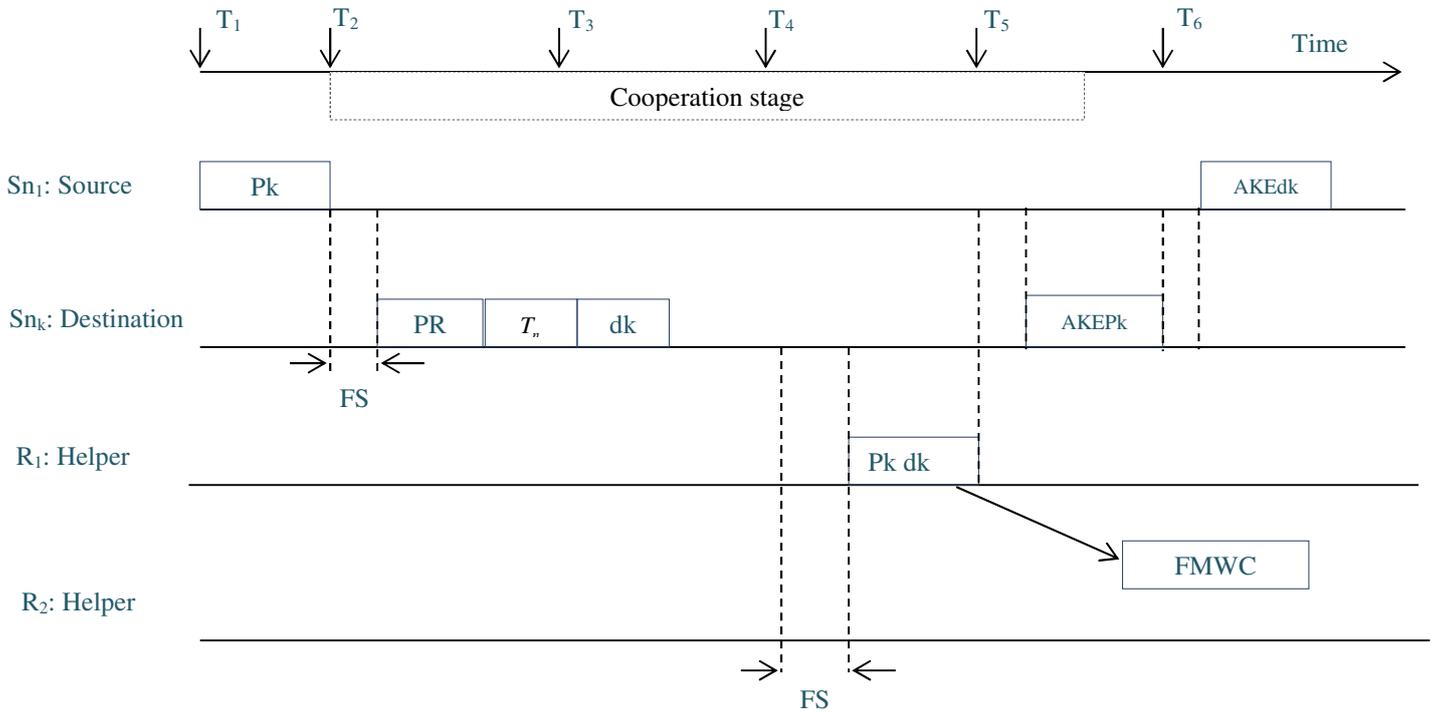


Figure 3: Network topology operation with a frame sequence

4.2 Fuzzy Mean Weighted Code (FMWC)

1) Mean weighted value calculation

The mean weighted value is calculated by multiplying the training data (TD) by the average trust value from section C. (5). Following the calculation of the score value, adaptive fuzzy logic is used.

$$S = \text{Mean} (t'_1 + t'_2 + t'_3 + t'_4 + t'_5 + t'_6) \quad (5)$$

Where, S is the Mean weighted value.

2) Fuzzy membership function

The process of defining 'crisp' inputs into fuzzy linguistic variables and linking them to membership values is referred to as fuzzy membership performance. The membership

function indicates the degree to which an element of the comprehensive set is related to the fuzzy set. Within the range of [0, 1], a fuzzy set will capture some value. Every score feature (input), as well as the difference in weighted events (input), was categorised into one of three levels: low, moderate, or high. A mathematical representation of membership performance is provided by Equation (6).

$$A_\alpha = \{x \in X | \mu_A(x) \geq \alpha\} = [\min\{x \in X | \mu_A(x) \geq \alpha\}] \quad \text{Where, } x = S \quad (6)$$

3) Fuzzy inference

For fuzzy inference, a collection of 'If-Then' logic assertions is necessary. A standard fuzzy rule is as follows:

$$IF \ x \text{ is } A \text{ AND } y \text{ is } B \text{ THEN } z, \quad (7)$$

The predecessors are A and B, while the successor is z. The mix of input variables determines the number of fuzzy rules. A pair of fuzzy rules was constructed in total. Table 3 provides an additional example of the principles. In equation, the max-min strategy is linked to fuzzy inferences (7).

$$\mu_A(x) = \max\{\min[\mu_1(x), \mu_2(x), \dots, \mu_n(x)]\} \quad (8)$$

4) Defuzzification

The final phase of a fuzzy system is defuzzification. The process entails converting the fuzzy inference results to a crisp number. As a result, the precise output is:

$$y = \frac{\int \mu(y) y dy}{\int \mu(y) dy} \quad (9)$$

If $y =$ If the R1 rule is chosen, the outcome will be '0'. The decision will be '1' if the = Rule id R2 is selected. In this case, the algorithm given;

<p>Input: Data Packet(Td) Output: Fuzzy rule set</p>
<ol style="list-style-type: none"> 1. Begin: 2. For each input Td do 3. Mean weighted value using (5). 4. Create fuzzy membership function using (6) 5. Fuzzy inference using (7 and 8). 6. Calculate final value y using (9) 7. //Generate rule id 8. If $y =$ S then 9. Generate Rule id R_i 10. Add a fuzzy rule in the rule set 11. Else 12. Repeat 13. End 14. End 15. End

Algorithm: 3 Fuzzy Mean Weighted Code

Finally, the encrypted data packet is securely delivered to the target node through the designated relay nodes. Figure 5 depicts the overall flowchart of the suggested method.

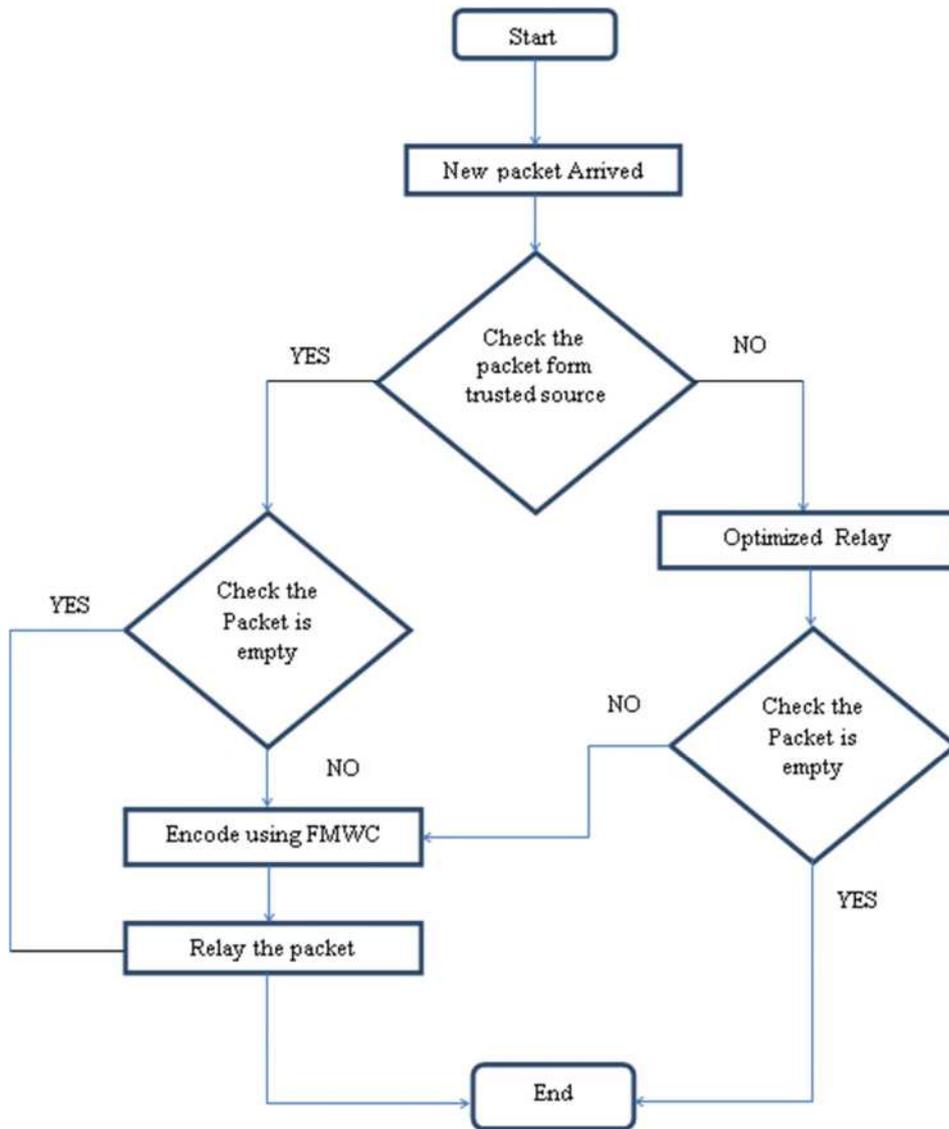


Figure 5: Flow chart of the proposed network coding

3.3 Scalable Enthalpy Artificial Neural-Network Based Grasshopper Optimization Algorithm (EANN-GOA) algorithm

Here, the enthalpy is used to select the best routing path. After that encoded the data packets Enthalpy perform the sum of the internal energy and the node pressure and volume of a thermodynamic system which is mathematically represented as follows equation (8),

$$E = I + PV \quad (8)$$

Here, $E \rightarrow$ enthalpy, $I \rightarrow$ internal energy, $P \rightarrow$ Network Average Energy, $V \rightarrow$ Node density.

3.3.1 ANN-based Grasshopper Optimization Algorithm

Then, as the input to ANN, use the computed enthalpy values. ANN is used to identify the best path for transferring data packets. In a nonlinear parallel approach called feed forward-back propagation, ANN learns from inputs and goal data. There are three levels to an ANN: input, hidden layer, and output layer. The number of features in the input data is represented by the nodes in the input layer, while the objective value of the dataset is represented by the nodes in the output layer. An ANN can build a nonlinear mapping between input and output based on the intricate connections between neurons in the hidden layer and the activation

function in each node. There are three layers in this image: an input layer, one or more hidden layers, and an output layer. Consider a three-layer neural network (m=3) with n_l neurons in the l th layer. Taken Straining samples $(U_s, T_s), s = 1, 2, \dots, S$, where $U_s = [u_1, \dots, u_{n_1}^s]$ and $T_s = [t_1^s, \dots, t_{n_M}^s]$. For certain inputs $U = [u_1, \dots, u_{n_1}^s]$ of the network, the input x_1^l and output y_1^l of i th neuron of the l th layer.

Input layer

$$\begin{cases} y_0^l = x_0^l \equiv 1, \\ y_j^l = x_j^l \equiv u_j \end{cases} \quad j = 1, 2, \dots, n_l \quad (9)$$

Hidden layer

$$\begin{cases} y_0^l = x_0^l \equiv 1, \\ x_j^l = \sum_{i=0}^{n_{l-1}} w_{i,j}^{l-1,l} y_{i,j}^{l-1}, \\ y_j^l = g(x_j^l) = \frac{1}{(1 + \exp(-x_j^l))} \end{cases} \quad j = 1, 2, \dots, n_l \quad l = 1, 2, \dots, M-1 \quad (10)$$

Whereas, $w_{i,j}^{l-1,l}$ is the weight from the i th neuron of $(l-1)$ th layer to the j th neuron of l th layer, and $g(\cdot)$ is the transfer function.

Output layer

$$\begin{cases} x_j^M = \sum_{i=0}^{n_{M-1}} w_{i,j}^{M-1,M} y_{i,j}^{M-1}, \\ y_j^M = g(x_j^M) = \frac{1}{(1 + \exp(-x_j^M))} \end{cases} \quad j = 1, 2, \dots, n_M \quad (11)$$

The weights $w_{i,j}^{l-1,l}$ of a neural network are changed during training to reduce the error function. The following is a commonly used training error function.

$$E = \sum_{s=1}^S E_s = \frac{1}{2} \sum_{s=1}^S \sum_{i=1}^{N_M} (t_i^s - y_i^{s,M}) \quad (12)$$

Where $y_i^{s,M}$ is the output of i th neuron of M th layer when inputting s th sample.

3.3.2 Algorithm for Grasshopper Optimization (GOA)

A population-based strategy, the grasshopper optimization algorithm. The natural behaviour and life cycle of grasshoppers can be used to solve optimization problems in this manner. The lack of exploration and exploitation balancing in meth-heuristics approaches is successfully overcome with this swarm intelligence optimization technique. Grasshoppers, like bees and ants, live in groups. The grasshoppers' community may be seen not only in adulthood, but also in the nymph stage, living in a collective style. A solitary grasshopper flies arbitrarily in the surrounding region in search of food; yet, once it joins the swarm, it goes incongruently to

the community in a predetermined course. Grasshoppers in nature search for food in rolling cylinder pathways, where they destroy agricultural crops. The following is a mathematical representation of grasshopper swarming behaviour.

$$x_i = S_i + G + A \quad (13)$$

Where does the I grasshopper fit in, The wind direction is A, and G represents the force of gravity pulling on the I grasshopper. In a group, S_i is the symbol for social interaction. Expand S_i , G, and A in the equation to get the following result: (eq 13).

$$x_i = \sum_{j=1, j \neq i}^N s(|x_j - x_i|) \frac{x_j - x_i}{d_{ij}} - g e_g + u e_w \quad (14)$$

where $s(r) = fe^{-r/l} - e^{-r}$ is a function simulating the impact of social interactions and N is the number of grasshoppers. $g e_g$ is the expanded G component, where g is the gravitational force and e_g is a unit vector pointing toward the center of the earth. $u e_w$ is the expanded A component, where u is a constant drift and e_w is a unit vector pointing in the direction of the wind. d_{ij} is the distance between the i and j grasshoppers and is calculated as $d_{ij} = |x_i - x_j|$.

The influences of wind and gravity are significantly weaker than the relationships between grasshoppers, hence this mathematical model should be changed as follows:

$$x_i = c \left(\sum_{j=1, j \neq i}^N c \frac{ub - lb}{2} s(|x_j - x_i|) \frac{x_j - x_i}{d_{ij}} \right) + T_d \quad (15)$$

Whereas ub and lb perform the upper and lower boundaries of the search space, T_d is the optimal solution value, and c is a decreasing coefficient that balances the exploitation processes, as follows:

$$c = c_{\max} - \text{iter} \frac{c_{\max} - c_{\min}}{Max_{\text{iter}}} \quad (16)$$

Where c_{\max} is the maximum value, c_{\min} is the minimum value, iter presents the current iteration and Max_{iter} is the maximum number of iterations.

Hybrid Grasshopper Optimization Algorithm

The weight was estimated with the help of an ANN. Then, using the GOA, optimise the weight in order to choose the best path for transmitting data packets from source to destination without causing traffic. Using a function that is a measure of the optimal performance quality of the response provided, this algorithm can concurrently find the best network structure and weights. The following is a formula for the grasshopper optimization algorithm-based approach of selecting the best path for the weights:

- Step 1:** A randomly selected population is used as a starting point. A random set of ANN weights characterises each member of the first generation.
- Step 2:** Using the weights associated with each individual, the ANN was utilised to determine the outputs for all S experimental inputs. The predicted outputs were then compared to the experimental data once more.
- Step 3:** The lowest E (neural network error values Eq) values were used to rank the population (12).
- Step 4:** The person in the population with the lowest E value (the best person) was passed down to the following generation.

Step5: Update the solution using the Grasshopper Algorithm after the fitness evaluation. We can revise the solution using equation (15). Mathematically, the grasshopper x_i 's circumstance or location can be described.

Step6. Reduce parameter c according to the iteration numbers to achieve a balance between exploration and exploitation. As the repetition progresses, this technique promotes an improvement in exploitation. Equation determines the coefficient c . (16). Figure 6 illustrates the overall ANN-GOA flowchart.

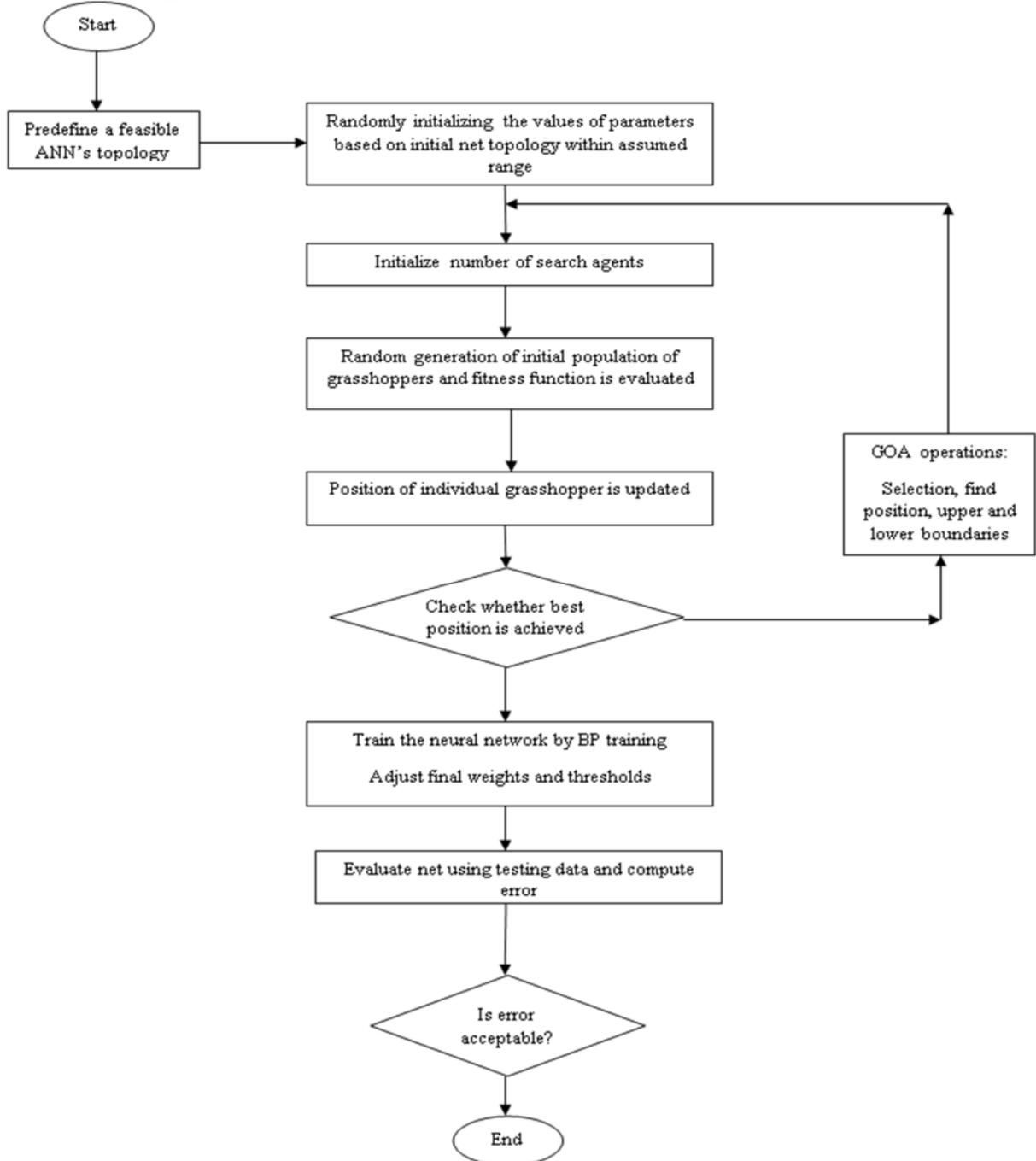


Figure 6: Flowchart of ANN-GOA

4. Result and Discussion

To simulate the specified protocol structure, the MATLAB software is utilised. Table 1 lists the simulation parameters. Around 200 sensor nodes are made and placed at random in a 1000 m x 1000 m region, each one spanning 100 m². In the initial stage of this work, the nodes are clustered using one hop and roughed using EANN-GOA. SEEP [21], EACRP [22], ME-CBCCP [23], and TDEEC [24] are then compared in terms of network throughput, end-to-end delay, packet delivery ratio, network lifetime, energy consumption, and scalability.

Table1: Simulation parameters.

Specification	Value
Area for simulation	1000 × 1000m
Range of node coverage	100m
ID of the node	16 bit
Size of a typical packet	50 bytes
Nodes in the graph	200
Time for simulation	500 s
Time between messages	0.02s
Protocol for the MAC layer	IEEE 802.15.4
The energy of nodes	100J

4.1 Network throughput

It is characterized because the most quantity of bit may be transmitted effectively inside one scheduled time. The full output of the system may be characterized because the total of the output that's created by the effective direct transmissions additionally to the output determined by the cooperation section when inaccurate packet receptions. This is precisely drawn as,

$$NT_{tot} = NT_D + NT_{co} \quad (17)$$

$$NT_D = (1 - \overline{PCE_{S \rightarrow D}}) * \frac{NP_{load}}{\overline{TN}_D} \quad (18)$$

$$NT_{co} = 2 * \overline{PCE_{S \rightarrow D}} * \frac{NP_{ld}}{\overline{TN}_{tot}} \quad (19)$$

In equation (17), the packet error rate is given by $\overline{PCE_{S \rightarrow D}}$, while NP_{ld} signifies the normal packet payload. Additionally, NT_D is the average time it takes for a single data packet to be transmitted and \overline{TN}_{tot} refers to the total amount of time it takes to complete a cooperative relay transmission. In terms of throughput, the suggested protocol is compared to the existing SEEP, EACRP, ME-CBCCP, and TDEEC protocols in figure 7.

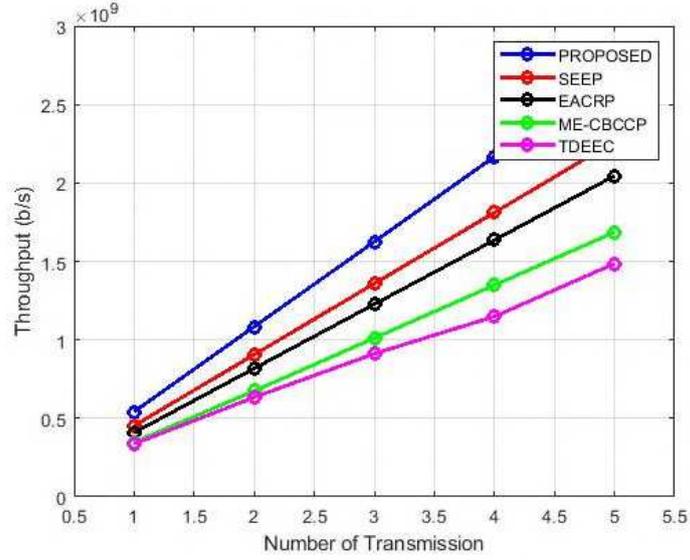


Figure7: Performance analysis of Network throughput

Figure 7 illustrates that NT_{tot} our proposed protocol outperforms the existing SEEP, EACRP, ME-CBCCP, and TDEEC protocols by a significant margin. The proposed value is 5.32×10^8 (b/s), while SEEP is 4.33×10^8 (b/s), which is comparable to the EACRP's 4.06×10^8 (b/s). With 3.37×10^8 (b/s) and 1.15×10^8 (b/s), the ME-CBCCP and TDEEC achieve the wickedest value.

4.2 End-to-end delay

The END_t is move on from the initial transmission till the proper reception within the destinations may be characterized as

$$END_t = NT_D + NT_{co} \quad (20)$$

Where NT_{co} is cooperative transmission through relays.

$$NT_{co} = NT_{min-delay} + NT_{additional} \quad (21)$$

Where, $NT_{min-delay}$ is the minimum average delay of schedule, $NT_{additional}$ is an additional delay. The evaluation graph of the proposed protocol with existing SEEP, EACRP, ME-CBCCP, and TDEEC protocols in regards of END_t is depicted in figure 8.

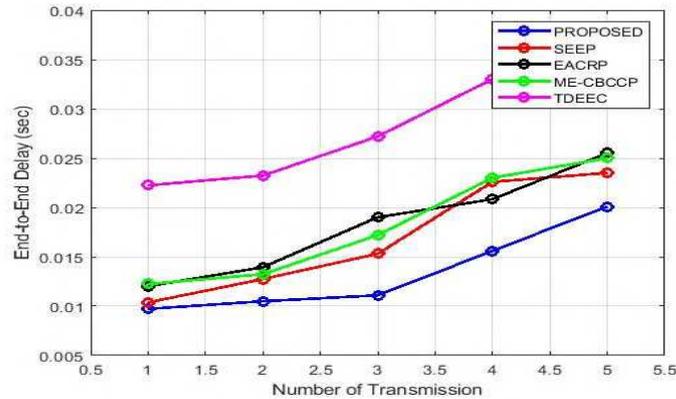


Figure 8: Performance analysis of End-to-end delay

Figure 8 shows that END_t , our proposed protocol END_t is 9.72×10^{-3} seconds which is expressively lesser than the existing SEEP, EACRP, ME-CBCCP, and TDEEC protocols. The END_t value of the existing SEEP is 0.010 seconds, EACRP achieves 0.012 seconds. The ME-CBCCP and TDEEC result in the wickedest END_t value with 0.012247 and 0.022257 seconds.

Our proposed protocol END_t takes 9.72×10^{-3} seconds, which is significantly shorter time than the existing SEEP, EACRP, ME-CBCCP, and TDEEC protocols (see Figure 8). The END_t current SEEP value is 0.010 seconds, whereas EACRP achieves 0.012 seconds. With 0.012247 and 0.022257 seconds, the ME-CBCCP and TDEEC produce the most terrible values.

4.3 Packet delivery ratio

The packet delivery ratio is the proportion of data packets received by destinations to those produced by sources. It's generally written as:

$$\overline{PKDR} = \frac{\sum PKT_{rcvd}}{\sum PKT_{gen}} \quad (22)$$

Where, $\sum PKT_{rcvd}$ is the totality of data packets received and $\sum PKT_{gen}$ is the totality of data packets generated.

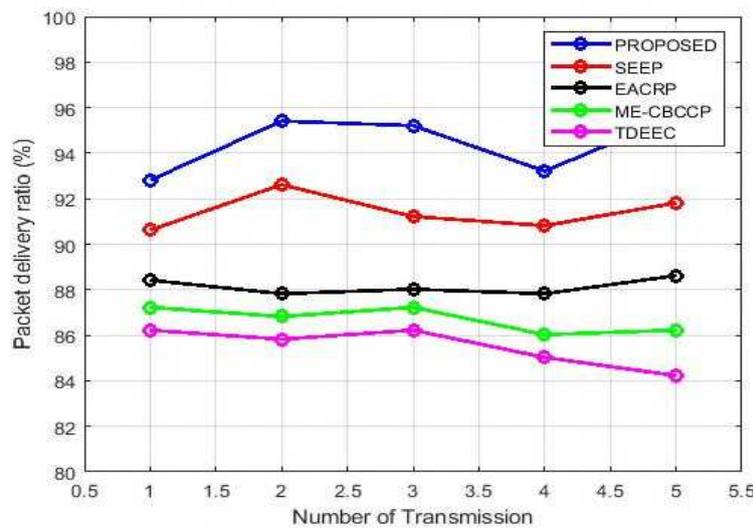


Figure 9: Performance analysis of Packet delivery ratio

Figure 9 shows that \overline{PKDR} our proposed protocol is suggestively better than the existing SEEP, EACRP, ME-CBCCP, and TDEEC protocols. The \overline{PKDR} of the proposed protocol is 95.81% and the existing SEEP is 92.62%, EACRP 88.62%. The wickedest \overline{PKDR} 87.22%, 84% is achieved for existing ME-CBCCP, and TDEEC.

4.4 Network lifetime

The residual energy of network nodes at every scheduling vacancy are referred to as network lifespan.

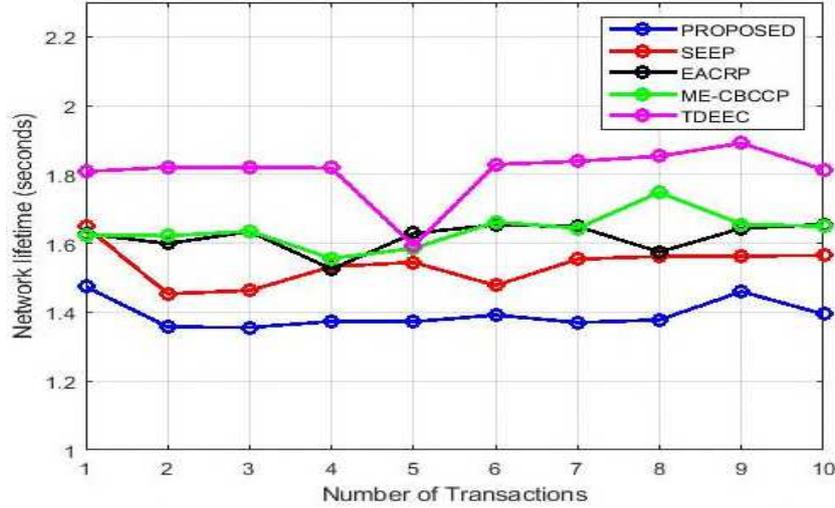


Figure 10: Performance analysis of Network lifetime

In figure 10 the network lifetime for the proposed protocol, and existing protocols SEEP, EACRP, ME-CBCCP, and TDEEC are plotted. Here the proposed protocol network lifetime is small compare to the existing methods that are determined.

4.5. Scalability

Figure (11) presents the performance analysis of the scalability. Compared with existing methods our proposed method outcomes the highest scalability to transfer packets. Compared proposed protocol, with existing SEEP, EACRP, ME-CBCCP, and TDEEC protocol

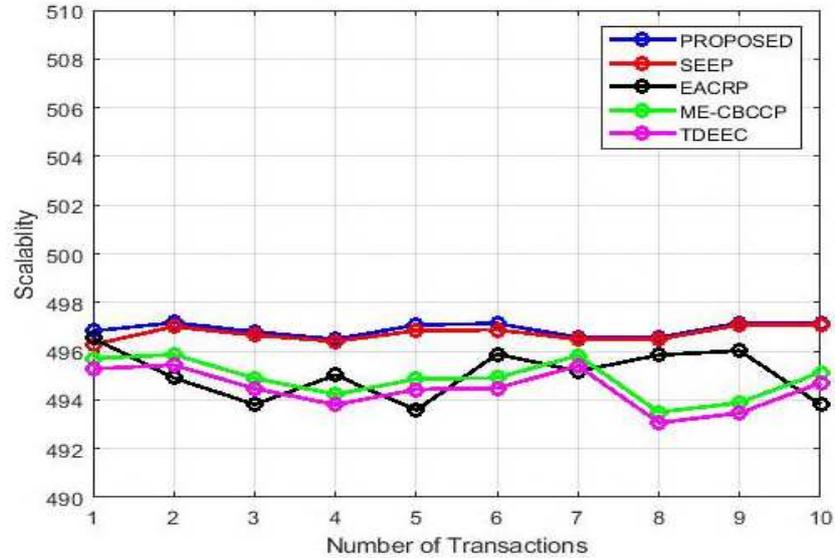


Figure 11: Performance analysis of Scalability

4.6 Energy efficiency

The energy consumption of three elementary energy efficiency potency procedures in demonstrating energy efficiency of each node as electronic communication, sensing, and information handling. Here the battery exhaustion procedure is spoken to as pursues

$$EN_i(t) = EN_i - \sum_{k=1}^t (EN_i^C(j) + EN_i^S(j) + EN_i^D(j)) \quad (17)$$

Where, EN_i is the battery's underlying energy in a specific situation time 0 and $EN_i(t)$ is the rest of the energy in a given time t for the smart thing i . $EN_i^C(j)$ is the shrewd thing's

communication energy, which refers to the amount of packets communicated. $EN_i^S(j)$
 $EN_i^D(j)$ Calculate the amount of energy used for each type of sensing and data processing.

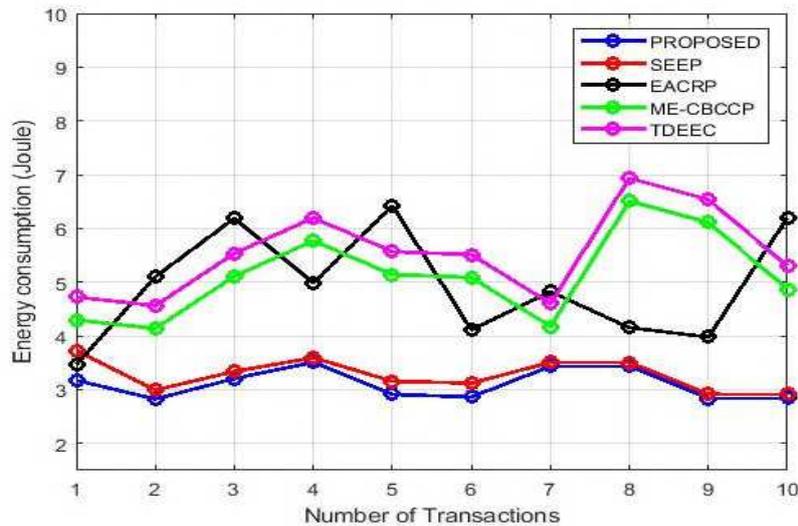


Figure 12: Performance analysis of Energy consumption

Figure (12) presents the performance analysis of the energy efficiency. Our proposed SSE protocol takes less energy to transmit the data packets.

5. Conclusion

The SSE routing protocol was defined in this paper, which is based on the Scalable, Secure, and Energy Efficient Routing protocol. It sends data packets from the source to the destination via the least congested path possible. Data from the cloud was initially acquired using a base station. The four parameters that go into picking a node (data packets) using a single-hop clustering approach are residual energy, distance to the sink, node density, and network average energy. The data packets are then encrypted with Fuzzy Mean Weighted Code (FMWC). The EANN-GOA method is then used to choose the least congested path from the source to the destination for data transfer. The proposed result is compared to a number of methods as well as some previous work. In comparison to previous research, our proposed methodology produces better results.

Declarations

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Data availability : Not applicable.

Ethical Approval : This article does not contain any studies with human participants or animals performed by any of the authors.

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