

Behavioral Based Uncertainty Handling in Energy Depletion Reduction (BUEDR) through Alleviation of Holes in an IoT Enabled Wireless Sensor Networks



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Abstract: In current era the usage of Internet is gradually improvising from Internet of People to an Internet of Things (IoT). Through the gateway, Wireless Sensors Networks (WSN) are integrating things to the Internet. But there are two major elements which affect the performance of the network, the presence of void hole and energy hole. Due to the unavailability of forwarded nodes, a particular region may suffer from void hole. In addition, if the load of data is not correctly balanced among the sensor nodes, then energy hole occurs. To overcome these issues, the proposed work uses a threefold behavioral based uncertainty handling transmission policy. In the first fold, the area of WSN is divided using voronoi diagram, which resolves the geometric relationships between sensors and to distribute transmission uniformly over the network area. The second fold alleviates energy hole vagueness in an adversarial environment by gathering information about the node denoted by intuitionistic fuzzy domain based cluster head selection to enhance energy dissipation. The third fold is optimal route selection for which fuzzy fish swarm optimization is adopted. From the simulation results, it is observed that the energy consumption achieves its superiority by hole alleviation and thus maximizes the network life time.

Keywords: Fuzzy fish swarm, Hole Alleviation, Intuitionistic fuzzy, IoT, WSN.

I. INTRODUCTION

The development of Internet has tremendously increased the connectivity of human at a large scale. The connectivity of devices along with humans has paved the way for introduction of Internet of Things paradigm. IoT implants intelligence in the environment by collecting and transforming the data into form of intelligent information. One of the essential component of IoT is WSN. WSN is comprised of self-autonomous nodes which are deployed deterministically or randomly in the sensing area. The role of the sensor nodes is to collect the information of interest and transmit it to the base station.

But a major cause which influences nodes is that they are battery operated. The network life time completely relies on the data load distribution on the sensor nodes. When there is an imbalance transmission of data packets, it may lead to quick energy depletion among intermediate nodes and consequently in the early expiry of network lifetime [1].

Irregular energy consumption among intermediate nodes is not the only cause for occurrence of holes, another strong factor is the randomness in deployment of nodes. Mobility of nodes may break the path among nodes that they often go to sleep mode to save energy. Excess requests to neighbor nodes is another important factor.

In general, WSN can be categorized as either homogenous or heterogeneous networks. In homogenous WSN, all the sensor nodes have equal characteristics like energy, sensing range and processing speed. While in heterogeneous WSN, characteristics of each node vary in energy, sensing range and processing speed [2].

Each routing protocol has to follow the below ideas to produce the optimal result.

- A routing protocol must be designed in such way that it finds an optimal energy consumption path.
- Appropriate control of traffic must be a prominent characteristic of such optimal routing scheme, because heavy traffic may lead to more energy depletion.

IoT enabled WSN have two major issues which degrades the performance of the network. They are void hole and energy hole which decreases the life time of the network. The void hole happens because of forwarder nodes unapproachability. And the cause of energy hole is due to imbalanced data traffic load among intermediate nodes.

A. Contribution

To overcome alleviation of void and energy hole, the proposed work enriches the lifetime maximization of IoT enabled heterogeneous WSN by introducing three stage transmission policy for handling uncertainty and to alleviate hole in WSN. In the first fold, it divides the coverage area using Voronoi diagram. In second fold it performs selection of forwarding nodes (cluster head) by intuitionistic fuzzy inference system. The third fold introduces optimal route selection from the cluster head to the base station using fuzzy fish swarm optimization.

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- To perform the transmission process evenly, the coverage area is divided and conquered using voronoi diagram which greatly enhances the relationship among sensors in geometric representation.
- The process of selecting forwarding nodes is done by introducing an efficient balanced energy distribution clustering approach based on intuitionistic fuzzy approach with non-uniform distribution. While performing cluster head election, this work takes nodes' energy, nodes' degree and neighbor nodes' residual energies into consideration as the input parameters. In this scheme, each sensor node calculates the probability of being a Channel Head(CH) with the help of Intuitionistic fuzzy inference system in a distributed way. This approach alleviates void hole in IOT enabled WSN.
- After selection of cluster heads for transferring the data packets, the route optimization is done using bio-behavioral approach. In this work the fuzzy artificial fish swarm optimization is adapted for finding the optimal route selection among cluster heads in wireless sensor networks. This approach overcomes the energy hole alleviation in an IoT enabled WSN.

II. RELATED WORK

There are many existing literatures which have reported the problem of energy efficiency through different approaches like conventional clustering, grid, chain, heuristic methods for clustering and multi criteria clustering. The aim of these approaches is to enhance the usage of resources to extend the life time of a network. Few of them are discussed in this section.

[3] proposed a hole repair algorithm in a distributed manner. In this, the movement of sensor nodes are considered and each node verifies its status to know whether they belong to hidden cross triangles or non-cross triangles in order to reduce overlapping. It fills the coverage hole by moving the neighbor node which has highest overlap region. [4] eliminates energy hole by implementing super nodes to the region which are closer to sink. Once the super nodes on the boundary region of the sink gathers all the data, then the nodes near the sink turn on their scheduling power and thus it enhances energy consumption. [5] proposed energy consumption model in a ring structure, which defines load of traffic and consumption of energy. From the observation it is noted that sensor nodes which are closer to sink consumes more traffic compare to other sensors nodes.

[6] proposed a scheme which overwhelms energy hole. In their work they adapted sleep scheduling mode conserving energy in WSN. Maximum distance nodes are nominated for computing the maximum energy for broadcast of data. An energy threshold is well-defined. If the energy level of a node drops below the threshold, then it cannot transfer data packets. This approach has the ability to maximize lifetime of network and stability period in cost of delay. [7] introduced an improved hole detection healing and replacing algorithm for optimal coverage in WSNs in order to maximize network lifetime through accumulating probability of loss of packet. [8] determined weighted probability of each sensor node to elect a node as cluster

head in a WSN environment. The presences of variation in cluster count produced cluster with varying size.

[9] extended the work of [8] by sending significant information of the sender to the base station and keeping the other nodes in sleeping node. This protocol is application specific. [10] formulated source driven sensor network protocol which selects cluster heads using neighboring nodes residual energy. This protocol is time consuming and creates uneven cluster size because of its variable cluster count. [11] proposed a method to improve the utilization of energy of sensor nodes for traffic control, energy consumption and increasing life time by adapting credit based energy efficient routing algorithm. It selects the cluster head based on the priority of relay sensor nodes. To overcome issues in energy consumption clustering it performs redundancy discovery and sleep algorithm is utilized.

[12] proposed a cluster based approach for finding redundant sensor nodes in WSN. When the data transfer rate is less than the predefined threshold value, then a clustering sleep scheduling algorithm is initiated to overcome the collision problem by making all other nodes in the cluster to sleep mode. [13] developed a secure hybrid routing protocol to select the cluster head based on their weight factors and a greedy forwarding method to select the best route. It secures packets using both symmetric and asymmetric cryptosystem.

From this literature study, there is no proper proof on handling vagueness to alleviate the coverage hole and energy hole in an IoT enabled WSN. Thus this paper aims at developing such an approach by adopting three different schemes.

III. PREAMBLE OF INTUITIONISTIC FUZZY SET(IFS)

The Membership degree $\mu(x)$, $x \in X$, alone is considered in fuzzy set which lacks to handle the issue of uncertainty in determining energy efficiency and load balancing in WSN. Hence this paper realizes the importance of processing uncertainty in adversarial environment specifically for efficient energy load balancing and alleviation of holes in WSN. The Intuitionistic fuzzy set (IFS) devised by [14-15] represents each element in the term of membership $\mu(x)$, and non-membership $\nu(x)$. An intuitionistic fuzzy set A in X, is inscribed as in (1):

$$A = \{x, \mu_A(x), \nu_A(x) | x \in X\} \tag{1}$$

where both $\mu_A(x)$, $\nu_A(x)$ value ranges from 0 to 1 with the condition as in (2):

$$0 \leq \mu_A(x) + \nu_A(x) \leq 1 \tag{2}$$

If the value of non-membership degree $\nu_A(x) = 1 - \mu_A(x)$ then it becomes fuzzy set, but a special case in intuitionistic fuzzy sets. [14-15] is an introduction of hesitation degree, $\pi_A(x)$ which is considered as an important factor when there is a lack of knowledge in defining the membership degree and it is formulated as in (3):

$$\pi_A(x) = 1 - \mu_A(x) - \nu_A(x); 0 \leq \pi_A(x) \leq 1 \tag{3}$$

Owing to hesitation degree, the value lies between $[0 \leq \mu_A(x), \mu_A(x) + \pi_A(x)]$.

Generally, intuitionistic fuzzy interpretation uses an Intuitionistic fuzzification, inference model and de Intuitionistic fuzzification and generate rules, instead of Boolean logic. The IFS rules are normal if-then rules which is represented as:

If D is low and E is high, then Y is medium
where, D and E are input variables, Y is a resultant output.

IV. PROPOSED METHODOLOGY OF BUEDR

The detailed flow of the proposed scheme is shown in the Fig. 1.

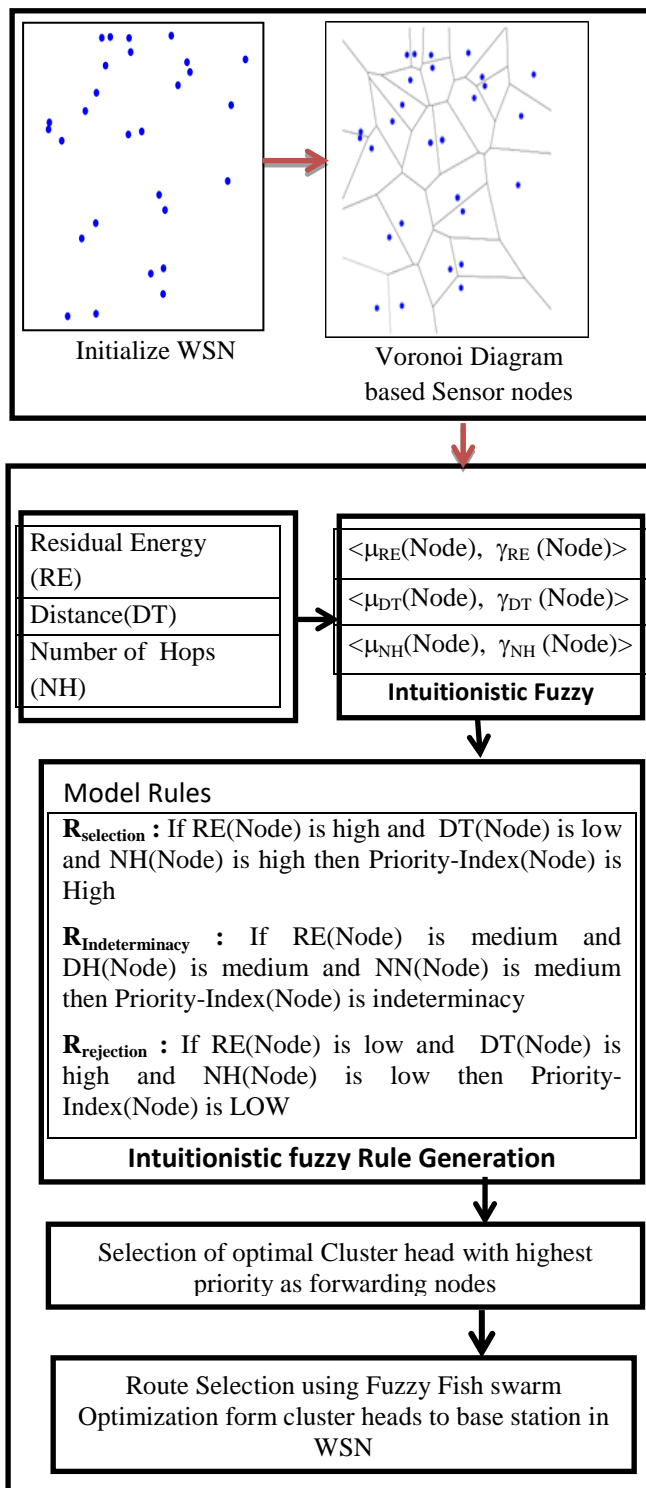


Fig. 1. Overall framework of alleviation of holes in Wireless Sensor Networks

A. Coverage Hole Detection Using Voronoi Diagram

The first step is to construct the Voronoi diagram for the organized wireless sensor network with the composed locations of all the sensor nodes involved in simulation as shown in Fig 1. In this work the distance information from edges and vertices of its associated Voronoi cell is carried by each sensor node in the network [16]. Next is to identify the presence of cover holes. This algorithm comprised of two stages namely building Voronoi diagram and discovering presence of holes. The former is done by making the sink or base station in a centralized manner. The base station receives the co-ordinate values of each sensor nodes. After collecting the details, the base station understands the topology of the network and performs the formation of Voronoi diagram. The sensor nodes receive their corresponding vertex information from the base station which is done in a distributed manner. Finally, every sensor node computes the distance between itself and the edges and vertices using Manhattan function of their associated Voronoi cell.

The sensors nodes infer nearby holes by matching the distance within the range of sensing. If it discovers a hole around a node, then it is referred as border node. These border nodes are involved in defining area of a hole. Algorithm given in Table-I, summarizes the steps for void hole discovery using voronoi diagram.

Table- I: Algorithm for void hole discovery using Voronoi diagram

1. The Voronoi cell's (V_1, V_2, \dots, V_n) location that is vertex coordinates are acquired by sensor node involved in discovery of hole.
2. For each voronoi cell
3. Compute the remoteness among the sensor node and V_i as DT_v ;
4. Compute the remoteness among the sensor node and the edge V_{ed} as DT_E
5. If ($DT_E > R_s$ or $DT_v > R_s$), where R_s is the relative coordinate of the sensor then it tags the current sensor node as hole boundary node;
6. End for loop

B. Proposed System Components of IFS

Our proposed IFS for security attack detection in WSN uses the mamdani inference method [14-15]. There are three main components in the system namely the intuitionistic fuzzifier, intuitionistic fuzzy inference engine and the intuitionistic defuzzifier.

Input: The model starts with the three inputs namely residual energy(RE), distance(DT) and number of neighbor nodes(NH) in the form of crisp value. Intuitionistic Fuzzifier: In this process, for each node, the given three input attributes have to be converted to intuitionistic fuzzy values by finding the membership and non-membership function.

Fig. 2 and 3 shows the membership function and non-membership function for the input attributes. The membership value of each attribute of the nodes are assigned as in (4).

$$\mu_A(x) = \begin{cases} 0 & ; x \leq a \\ \left(\frac{x-a}{b-a}\right) & ; a \leq x \leq b \\ \left(\frac{c-x}{c-b}\right) & ; b \leq x \leq c \\ \in & ; x \geq c \end{cases} \quad (4)$$

and non-membership value of each attribute as in

$$\vartheta_A(x) = \begin{cases} 1-\in & ; x \leq a \\ 1 - \left(\frac{x-a}{b-a}\right) & ; a \leq x \leq b \\ 1 - \left(\frac{c-x}{c-b}\right) & ; b \leq x \leq c \\ 1-\in & ; x \geq c \end{cases} \quad (5)$$

The output variable of intuitionistic fuzzy decision making system with the membership and non-membership function. for output of cluster head selection is depicted in the Fig. 4. and Fig. 5.

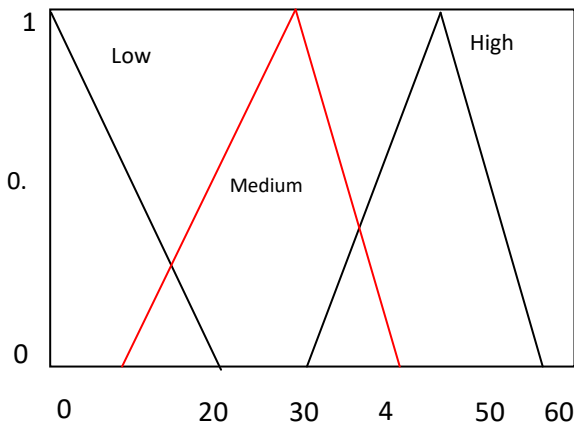


Fig. 2. Membership function of input attributes

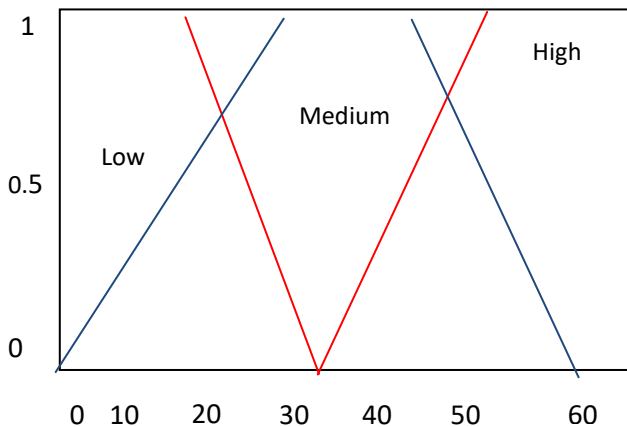


Fig. 3. Non-membership function of input attributes

The intuitionistic fuzzy values are handled by the inference engine in the terms of membership, non-membership and hesitation degree of each input attribute

and the rules are framed using IF-THEN rules and yields the output of the fitness of specific node as cluster head. The input criteria for selecting a cluster head are residual energy, distance and the number of neighbor nodes within its cluster. The rules are generated using logical operators like AND, OR and NOT in the form of intuitionistic fuzzy logical operator using MIN-MAX strategy. The portion of the rule of intuitionistic fuzzy before THEN is called predicate or antecedent, while the portion subsequent to THEN is referred to as consequent. The integrated truth of the predicate is identified by intuitionistic fuzzy set implication rules such as MIN-MAX [15] with bounded arithmetic sums. Each and every rule in the rule-base is developed in a parallel manner by the intuitionistic fuzzy inference engine. Any rule that fires is put final into intuitionistic fuzzy solution space.

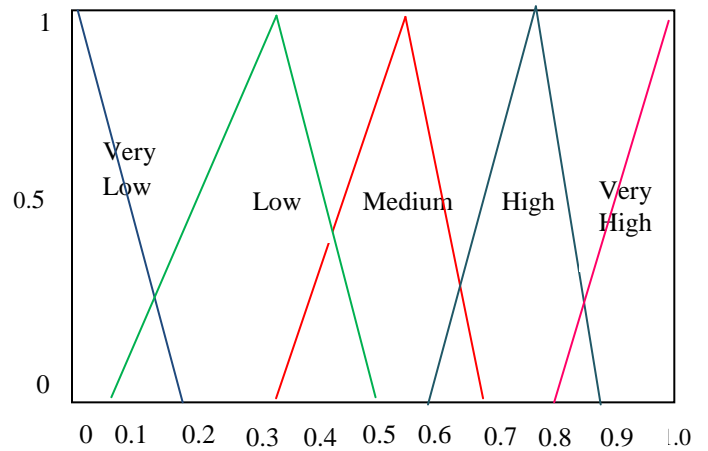


Fig. 4. Membership function for output

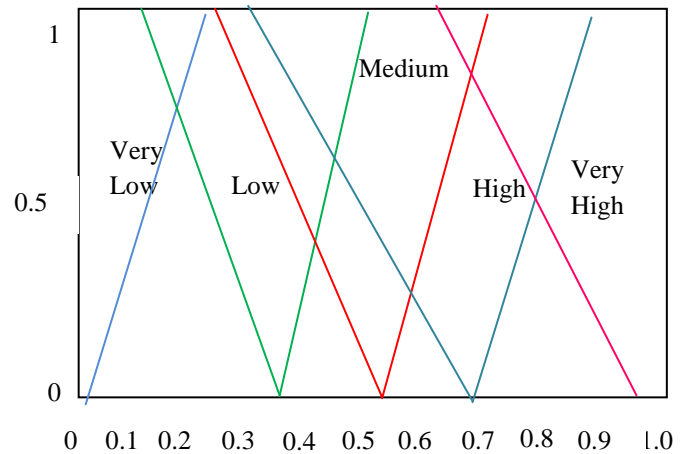


Fig. 5. Non-membership function for output

To describe the working principle of the intuitionistic fuzzy controller, the sample values listed in Table-II shows the degree of membership and non-membership value of three input attributes namely residual energy, distance and number of neighbor nodes.

Table-II: Sample values for membership and non-membership input attributes

| Membership values for Input Features | Non-membership values for Input Features |
|---|---|
| Residual Energy: $\mu_{low}(x)=0$ $\mu_{medium}(x)=0.7$ $\mu_{high}(x) = 0.3$ $\mu_{Residual_Energy} = \{0, 0.7, 0.3\}$ | Residual Energy: $v_{low}(x) = 0.7$ $v_{medium}(x) = 0.2$ $v_{high}(x) = 0.08$ $v_{Residual_Energy} = \{0.7, 0.2, 0.08\}$ |
| Distance: $\mu_{low}(x) = 0$ $\mu_{medium}(x) = 0.4$ $\mu_{high}(x) = 0.8$ $\mu_{Distance} = \{0, 0.4, 0.8\}$ | Distance: $v_{low}(x) = 0.9$ $v_{medium}(x) = 0.6$ $v_{high}(x) = 0.2$ $v_{Distance} = \{1, 0.5, 0.18\}$ |
| Number of neighbor nodes $\mu_{low}(x) = 0$ $\mu_{medium}(x)=0.54$ $\mu_{high}(x) = 0.67$ $\mu_{No.of.Hops} = \{0, 0.54, 0.67\}$ | Number of neighbor nodes $v_{low}(x) = 0.49$ $v_{medium}(x) = 0.26$ $v_{high}(x) = 0.38$ $v_{No.of.Hops} = \{0.49, 0.26, 0.38\}$ |

C. Intuitionistic Fuzzy Inference Engine

This process is the real brain as the logic of this proposed algorithm resides. The interpretation of intuitionistic fuzzy rule is an if then model along with assignment of weight, which signifies the truthiness of rules. The conditional statements that which are represented in IF-THEN rule combinedly known as intuitionistic fuzzy logic. The inference engine fires the suitable IF-THEN rules in the knowledge base [15]. Intuitionistic fuzzy set rules are defined as follows:

Rule: IF <<condition>> THEN <<resultant>> [wt] (6)
where,

- <<Condition>> which is a combination of intuitionistic fuzzy logic operators and its expressions
- <<resultant >> is a nuclear expression, and
- *wt is a depiction of rule’s confidence which is the real number referred as weight*

Intuitionistic fuzzy rule generated for optimized route selection includes:

- If Node_i(RE) is high and Node_i(DT) is low and Node_i(NH) is high then Node_i(Cluster_head) is high.
- If Node_i(RE) is low and Node_i(DT) is high and Node_i(NH) is low then Node_i(Cluster_head) is low.
- If Node_i(RE) is medium and Node_i(DT) is medium and Node_i(NH) is medium then Node_i(Cluster_head) is indeterministic.
- If Node_i(RE) is medium and Node_i(DT) is high and Node_i(NH) is medium then Node_i(Cluster_head) is indeterministic.
- If Node_i(RE) is high and Node_i(DT) is low and Node_i(NH) is low then Node_i(Cluster_head) is low

Like the aforementioned sample rules, all the possibilities are derived and the rules with low cost are determined for

optimal path selection and it is fired on the input space to produce the best route discovery options from the source to the base station via cluster heads.

D. Optimal Route Selection using Fish School Search Optimization

After the selection of cluster heads in each cluster, then the data has to be collected from other non-cluster heads within the cluster and has to be aggregated by the cluster head to transmit the data packets to the base station. In this work, to transfer the data to the base station, the cluster heads have to select the optimal path which is done by adapting an optimized behavioral based approach. It is greatly inspired by the swimming fishes which expand and contract while they are in search of food. The nature of fish school search optimization [17] is to find the nodes which are nearer to the cluster head and that have high residual energy to advance/forward the data packets to the base station. Such optimal cluster heads which are involved in process of transmission are determined using the fish swarm intelligence. This algorithm makes use of weights for all the fishes to find an optimal shortest path selection from the cluster heads to the base station is considered. Procedure for fish school search based path selection are

1. Apply fish School Search algorithm for suboptimal solutions in selected cluster heads
2. From the selected cluster initialize the parameters
 - N: number of fish in artificial fish,
 - δ : Crowding factor, defined as the bandwidth where the fish on artificial path.
 - Visual: Sensing range of artificial fish, as defined in the network for the artificial fish can perceive neighbors.
 - Step: The length of artificial fish moving step from one node to its neighbor nodes
 - x_i (i = 1,2,...n): For optimization of the variables, corresponding to the optimal path in the network
 - $y = f(x)$, y is the objective function, corresponding to the concentration in finding shortest optimal path. When the path is shorter the expense and delay will be low.
3. While stop criterion is not met do
4. for each fish do
5. Artificial fish is assigned to the current cluster head node whose distance to the neighboring nodes must be lower and the energy must be high for transmission of data in an optimal way
6. Feeding Action:
 - (a) Provided $p = 0$, the current status set to artificial fish is x_i ;
 - (b) The implementation of $x_j = \text{Random}(N(x_j, \text{visual})$ to generate a new state
 - (c) If $f(x_i) < f(x_j)$, the state of the artificial fish will be amended as in (7):

$$x_i \leftarrow x_j + \text{Rand}(\text{step})(x_j - x_i) / \| (x_j - x_i) \| \quad (7)$$
 - (d) Otherwise, if $p < 10$, return to (6b) for implementation:
 - (d) Performing an arbitrary walk further:

7. From the state X_i , explore the number of partners n_f and central location X_c in current neighborhood $d_{ij} < \text{Vision}$. If $Y_c/n_f > \delta Y_i$, then the partners have more energy and the cluster has less distance, where Y_c is the average energy within the communication radius of the centre node c . So move one step toward the direction of the center of partners, otherwise implement the foraging behavior as in (8)..

$$X_{c,d} = \frac{1}{N} \sum_{i=1}^N X_{i,d} \quad (8)$$

8. The next position of the fish is decided as per (9)

$$X_i(t+1) = X_i(t) + \frac{X_c - X_i(t)}{d_{i,center}} X[\text{Visual } x \text{ rand}(0,1)] \quad (9)$$

9. Update Visual according to (10)

$$\text{Visual}(t+1) = \text{visual}(t) * (L_{low} + (\text{Rand} * (L_{high} - L_{low}))) \quad (10)$$

Table-III summarizes the proposed algorithm of behavioral based uncertainty handling in energy depletion reduction using alleviation of holes in IoT enabled wireless sensor networks. Before starting the process, initialize the parameters involved in both void hole and energy hole alleviation. To avoid void hole, the area of the network is divided using Voronoi diagram which creates a geometrical relationship among the sensor nodes and evenly distributes the nodes in it. The residual energy, distance and the number of hops are used for electing the cluster head using the intuitionistic fuzzy inference system that converts the crisp values to intuitionistic fuzzy domain values. With the inferred rule the nodes which have highest residual energy, minimum distance among neighbors and number of hops to transfer data are considered as factors for electing cluster head in each sub regions. Once the cluster head is elected then data from other sensor nodes within the cluster are collected and aggregated. The aggregated data is then transferred to the base station by finding an optimal route using fish school search algorithm. Once the path is selected then the cluster head starts transmitting the data to the base station and thus it avoids the energy hole among the nodes near the base station.

V. PERFORMANCE EVALUATION

The simulation was accomplished using NS2 software by deploying sensor nodes in a randomly dispersed manner in a square unit region of 100 x 100 which follows a consistent allocation. Each sensor nodes broadcast hello messages along with their local evidence to the base station. The preliminary quantity of clusters is predetermined by choosing potential value and changes continuously along node's density once the nodes started dies. Cluster with small size are merged with nearby big clusters. The node without energy constraint is known as base station (BS) improved with the capability of computation which is positioned at the middle of the arena. Table-IV gives the list of simulation parameters used.

In this section, the presentation of the anticipated system BUEDR and the prevailing schemes ODTs, LiMHA and EEAC is evaluated using simulation. All these models have same perspective of energy depletion reduction by determining cluster head and optimal selection of forwarding nodes.

Table- III: Proposed algorithm of BUEDR using alleviation of holes in an IoT enabled wireless sensor networks

| |
|--|
| Input: Residual Energy RE, Distance DT, Number of hops NH, Sensor nodes |
| Output: Determine cluster head and optimal path between cluster head to base station |
| 1. Initialize Factors |
| 2. Initialize and deploy the position of sensor nodes on the IOT enabled WSN |
| 3. Perform division of sub region in the network area using voronoi diagram |
| 4. Randomly select cluster head for each region in the network // Process to alleviate void hole by choosing forwarding nodes as cluster head |
| 5. For each round |
| 5.1 For each node in a sub region calculate DT(node), RE(node) and NH(node) |
| a. Convert the input crisp value to the intuitionistic domain values |
| b. Apply intuitionistic fuzzy inference engine to generate rules |
| c. Select the node as cluster head which has max(DS), max(RE) and min(NH) |
| d. Assign the node with highest priority as cluster head |
| 5.2 Each Cluster head collects data from the non-cluster head nodes and aggregate it // Process to alleviate Energy hole in WSN |
| 5.3 Apply Fish School Optimization based on the priority index and distance between cluster head to base station for selecting optimal route |
| 5.4 After determining optimal route, the data transmission takes place |
| 6. End of round |
| 7. while sink obtain data do |
| 8. Estimate global energy usage/consumption , node's life period at each iteration/round |

Table- IV: Simulation parameters

| Paramet er | Value | Description |
|-----------------|------------------------------|--|
| N | 100 | Number of nodes in WSN |
| E_0 | 0.5J | Node's initial energy |
| BS_{LOC} | 50,50 | BS location |
| ϵ_{fs} | 10 pJ/bit/m ² | Energy spent by the amplifier to be transmitted at a short distance |
| ϵ_{mp} | 0.0013 pJ/bit/m ⁴ | Energy spent by the amplifier to be transmitted at a longer distance |
| E_{elec} | 50 nJ/bit | Energy consumed in the electronics circuit to be transmitted or receive the signal |
| size(pkt) | 500 bytes | Data packet size |
| Msg | 25 bytes | Hello/broadcast/CH join message |

A. Performance Metrics

The succeeding recital metrics were cast-off to assess the performance of devised BUEDR method.

Packet Delivery Ratio: It is well-defined as the proportion of data packets acknowledged by the destinations to those produced by the sources

Average hops: The number of intermediate nodes involved in transmission of data packets between source to the base station

End to End delay: It is termed as average amount of time elapsed when the data packets leaves from the source node and received fruitfully by base station

Total Energy Consumption: During packet delivery process the energy consumed for transmission, receiving and idle time of each node in the whole network is considered.

B. Packet delivery ratio

To analyze the performance of the proposed BUEDR scheme with other existing schemes to enhance the energy consumption by alleviating the holes in IoT enabled WSN. The packet delivery ratio is one of the prominent measurement. With the varying size of the nodes in the network the transmission range was set to 1000m is taken into account for this simulation study. From Fig. 6., it is observed that due to the presence of holes in network there is high degree of energy depletion in the existing schemes because they fail to handle the border lying nodes. This proposed work considerably increased the ratio of packet delivery successfully due to its ability of diving the regions based on voronoi diagram and representing each node in terms of intuitionistic fuzzy domain and selecting optimal path using fish school search algorithm. The proposed approach selects the forwarding nodes with capability of determining the degree membership and non-membership in vagueness handling.

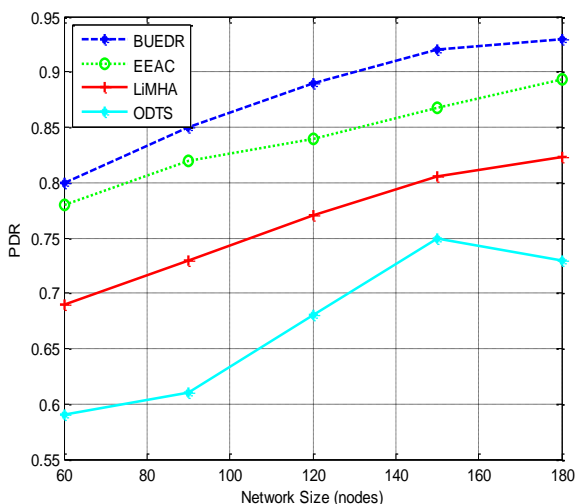


Fig.6. Performance comparison based on packet delivery ratio

C. Average hops

In this subsection, the analysis of the proposed BUEDR is subjected to average number of hops involved in packet transmission among cluster head and the base station. The

transmission ranges from 600m to 1000m. From figure 7, it is observed that the total number of intermediate nodes involved in data transmission is greatly reduced by the proposed approach. While adapting the proposed scheme with inferred knowledge of intuitionistic fuzzy domain and the fish school search based route selection, the nodes with higher residual energy and minimum distance are considered as the highest priority nodes for participation in data transmission from Fig. 7.

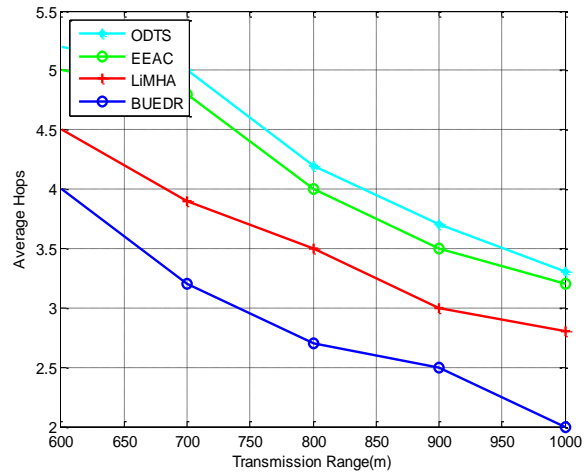


Fig. 7. Performance comparison based on average hops

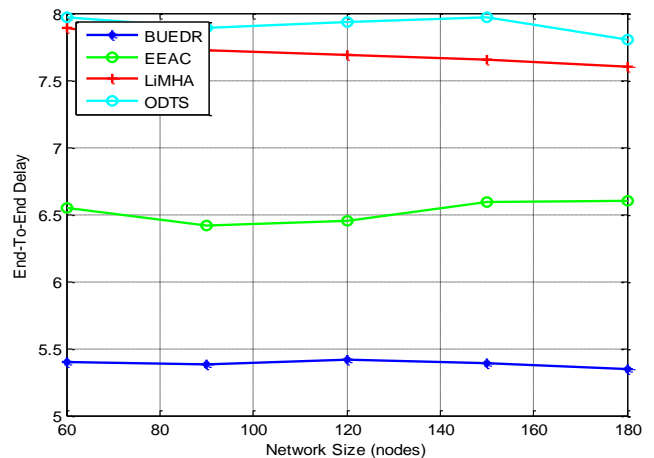


Fig. 8. Performance comparison based on end to end delay

D. End to end delay

Fig. 8., illustrates the End to End delay (E2E) of the proposed BUEDR and the existing schemes ODTs, LiMHA and EEAC. The end to end delay often occurs when there is an unbalanced load of traffic. The proposed approach reduces the E2E delay considerably by alleviating the void and energy holes. It is done by discovering void holes through voronoi diagram and distributing the sensor nodes to cover entire network uniformly. The energy depletion of the nodes is greatly handled by adapting the cluster head selection to intuitionistic fuzzy inference system and applying fish school search method to optimize the process

of packet transmission from the cluster head to the base station in an effective way. By considering uncertainty handling of selected cluster head nodes as forwarding nodes, the data packets are aggregated by these cluster heads before transmission. But all these factors failed completely in the existing schemes.

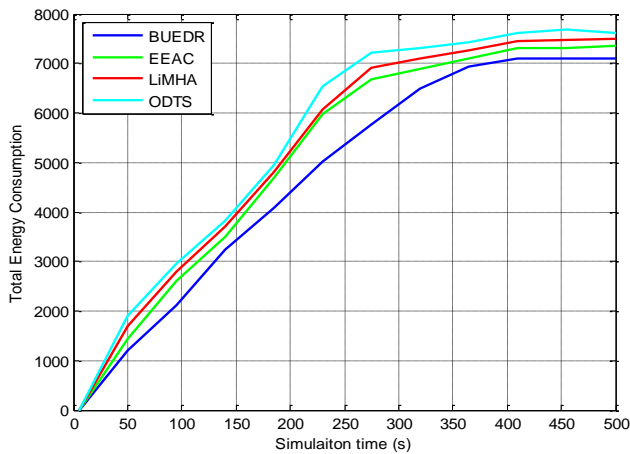


Fig. 9. Performance comparison based on total energy consumption

E. Total Energy Consumption

The total energy consumed is obtained by considering the transmission energy, reception energy and the idle energy consumed by the IoT enabled WSN. The actual behavior of the routing scheme is clearly depicted in Fig. 9. From the figure, it is clearly evident that the proposed BUEDR consumes very less energy while comparing ODTS, LiMHA and EEAC. BUEDR handles the void hole and energy hole very intellectually with its intuitionistic domain knowledge and behavioral based route selection. It helped in hole alleviation and selecting more optimistic nodes which have less holding time and high energy. Thus the nodes never suffer from the packet collision or battery power depletion.

VI. CONCLUSION

This paper proposed a behavior based transmission strategy that is capable of alleviating the holes in order to increase the network lifetime specially in case of vagueness in handling selection of cluster heads. The deployment of heterogeneous type of sensor nodes in each sub region partitioned by voronoi diagram proves its success rate by balancing the node distribution evenly and balancing the load among cluster heads by representing them in terms of degree of membership, non-membership and indeterminacy. It achieves its high degree of transmission rate with increased life time of the IoT enabled WSN. The existing techniques ODTS, LiMHA and EEAC greatly failed to handle the vagueness in selection of cluster head and optimal route selection. They just considered the conventional metrics to overcome the energy depletion problem in WSN. The proposed BUEDR proves the improvement in load estimation at every hop to provide an efficient and optimal route selection to reach the base station or destination. Through Voronoi diagram, it was able to compute a feasible region. The energy consumption within that region helped to discover coverage hole and to operate on sensor nodes to distribute them based on its geometric

relationship. In addition, the reason for increased network lifetime is selection of optimal route for packet transfer from the cluster head to the base station. The fish schooling paradigm allows the node to exploit its energy resources entirely. The effectiveness and validity of the proposed work are shown through simulations. Results of BUEDR also revealed that the anticipated work gives best performance results over the existing counterparts in terms of alleviation of holes, increased network lifetime and enhanced energy consumption.

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