Handling of Indeterminacy for Trust Aware Energy Consumption Using Adaptive Intuitionistic Fuzzy Environment in Wireless Sensor Networks

N. Geetha Lakshmi, D. Shanmuga Priyaa

Abstract: In Wireless Sensor Network Environment (WSN), the most critical parameter of sensor nodes is the optimal usage of life time. An efficient WSN protocol needs to conserve energy as the main objective of maximizing the network lifetime. Further, secure topology construction is also included in this work, because trust value is considered as a vital factor which affects the behavior of nodes. The incompletion or inconsistency in gathering information of sensor nodes is not well-handled in most existing techniques for the selection of cluster head, taking into account trust Value, Residual Energy, Shortest Path (distance), and Number of Neighbor Nodes. This paper has devised a two-stage optimized energy consumption scheme termed AIFMDMCS. This work elects cluster heads under the condition of indeterminacy in selection criteria with the aid of Intuitionistic fuzzy Logic based decision making. These cluster heads are responsible for collecting and integrating the data received from cluster nodes. The integrated data packets are transferred to the base station using Intuitionistic fuzzy inference engine for improved load balancing, in case of high traffic and presence of collision detection. The simulation results demonstrate that this approach is more effective in protracting network lifespan, because in WSN, it finds the optimal shortest route, and, during vagueness while electing both cluster heads, the degree of indeterminacy is considered.

Keywords: Wireless Sensor Networks, Energy Consumption, trust aware, Cluster Head Selection, Intuitionistic Fuzzy Logic, Uncertainty, indeterminacy

I. INTRODUCTION

Wireless Sensor Network (WSN) is generally used for sensing, collecting and forwarding the data Wireless sensor networks in grouping a large amount of smaller sensor nodes. The sensor nodes are placed randomly or manually into the specified area. The power consumption of the sensor nodes and lifetime of networks are the most challenging issues in the WSN environment [27]. In WSN, clustering is one of the most challenging issues and can be mainly focused on for improving scalability to enhance the lifetime of the network. Initially heuristic approaches were used. The main drawback of this approach is that it will select a node with a very low energy. Later Meta heuristics approaches were used, which could deal directly with the gateways and manage them to the maximum energy of the nodes [28, 29]. Sensor nodes are energy constrained. Once the node is deployed it cannot be recharged further. The characteristics of WSN's are battery operation, short range communication and nodes with no limited central manager. Improving network lifetime is the fundamental challenge of wireless sensor networks [27]. The sensor nodes consist of low power, and an irreplaceable battery which has a limited lifetime. Sensor nodes typically use irreplaceable power with the limited capacity, and the node's capacity of computing, communicating and storage is very limited. This feature of sensor nodes requires WSN protocols to conserve energy which is the main objective of maximizing the network lifetime. In order to accomplish extended lifetime of the WSN, it is essential to utilize the energy consumption of the sensor node precisely and discover the shortest path for transferring the data packets to the base station more resourcefully. In most real time applications, the information of the sensor data is really vague to collect because of the frequent changes due to their mobility. However, there are several existing techniques available for energy consumption-based routing techniques. There is no complete proof to provide better optimization in case of uncertainty in selection of cluster head which itself contains imprecise data. This paper has devised an Adaptive Intuitionistic Fuzzy Multi-Attribute Decision-Making (AIFMADM) for overwhelming those two challenges in two different stages.

Stage 1:

In this stage a prominent election of cluster head is done by considering indeterminacy as a major factor in situation of uncertainty during selection process among cluster nodes.

The criteria used for electing sensor node as cluster head are fixed using the degrees of membership, non-membership and hesitation for residual energy, distance among cluster nodes and the number of neighbor nodes. The node which has a high degree of membership towards these three criteria will be selected as cluster head.

Stage 2:

After the prominent cluster head is selected, the energy consumption should also be considered in route selection. Each cluster head should collect data from the cluster nodes and aggregate and transfer them to Base Station. So, an enriched Intuitionistic fuzzy rule inference system is framed using the degrees of membership, non-membership and hesitation of residual energy, distance, delay,

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bandwidth and queue size for the finest route selection among cluster head nodes to reach the base station in case of high traffic and presence of collision detection. The simulation is done using NS2 to prove that this proposed optimal routing scheme consumes energy commendably.

II. RELATED WORK

In this section an elaborative study on various existing research works is done on Energy Consumption in wireless sensor networks using cluster head formation and route selection.

Dilip Kumar *et al*. [1] devised a scheme by assigning a different threshold to each node and based on the assigned weights to the nodes the cluster head is selected. On the basis of the life time of network and stability of the sink, the result showed that the proposed work performed better. Babar Nazir *et al.* [2] introduced an algorithm that used mobile nodes to fill the gap formed by any energy hole or hot spot. It was used so that we could use the energy in a balanced way through the network and increase the lifetime of the sensor network. Ben Alla Siad *et al.* [3] presented a model which evenly distributed the load of energy within the sensor nodes by performing adoptive clustering which balanced the leach protocol efficiently. This protocol reduces node failure probability through efficient consumption of energy. Rashed *et al.* [4] developed a protocol to enhance the sink stability of a sensor network. It also introduced a clustering scheme with a chain routing algorithm to enhance the energy and stable period constraints. By using this algorithm, the link between the cluster heads was framed.

Xiaojiang Du *et al.* [5] developed a method which held a large number of sensor nodes with low power and a low number of sensor nodes with high power. Here the network was assumed to be static and each node was aware of its location. Hence these techniques could not be adapted in more real time applications. Jung-Hwan *et al.* [6] introduced clusters with uneven size where clustering was dynamic and produced variations in size. Sanjeev *et al.* [7] developed an approach for clustering the heterogeneous sensor nodes to increase their life. The communication cost was reduced considerably. Incel *et al. [*8] handled false data collection in WSN, using Time Division Multiple Access (TDMA). It focused on scheduling process under tight time scheduling and produced high throughput under high load conditions. It reduced the bottle neck nodes for scheduling process by constructing spanning tree. Thus, it reduced the scheduling length of the process.

Xu *et al* [9] developed data aggregation in an efficient way by minimizing the delay. This work was collision free during data transmission in WSN. Kasbekar *et al* [10] introduced the techniques designed by polynomial-time used by a distributed algorithm. One of the significant advantages in distributed algorithm was that it could achieve maximum lifetime. Kajal *et al* [11] elected the RaSMaLai algorithm. This algorithm prolonged the network lifetime by load balancing and was also used to randomly switch a few of the selected sensor nodes to other paths which held fewer loads. Biswas *et al* [12] in their work proposed an energy efficient hierarchical routing protocol for Wireless Sensor Networks to increase the network lifetime. was proposed. They considered the critical issue as nodes could not be recharged and/or replaced frequently.

Tayeb *et al* [13] proposed to improve the utilization of energy of sensor nodes for traffic control, energy consumption and increase of life time by adapting credit based energy efficient routing algorithm which selected the cluster head based on the priority of relay sensor nodes. To solve this, an energy efficient cluster method with cluster-based redundancy discovery and sleep algorithm for energy efficient routing was proposed. Sree Vidya and Nagaraj [14] in their work proposed a cluster-based approach for finding redundant sensor nodes in WSN. When the data transfer rate was less than the predefined threshold value, then a clustering sleep scheduling algorithm was initiated by them to overcome the collision problem by changing all other nodes in the cluster to sleep mode. Muthusenthil and Kim [15] in their work developed a secure hybrid routing protocol for selecting the cluster head based on their weight factors, and greedy forwarding method was used for selecting the best route. It secured packets using both symmetric and asymmetric cryptosystem.

Din *et al* [16] proposed cluster head selection using multi-tier algorithm using fuzzy logic which used sensor nodes consistently, and the nodes died consecutively as the data enlarged. For these reasons the sensor nodes consumed their energy effectively hence persisting with the wireless network lifespan. Guihaichen *et al.* [17] formulated a source driven sensor network protocol which selected cluster heads using neighboring nodes' residual energy. This protocol was time consuming and held an uneven cluster size because of its variable cluster count. Marin *et al.* [9] framed a cluster with a low construction and maintenance overhead. Each node in the cluster was set to a unique weight and unique identifier. A node with the highest value was elected as the cluster head. Chong Wang *et al.* [18] introduced the protocol which saved the cost of energy by splitting large clusters into smaller ones using sub cluster head. It increased the network life time by activating a single node which was involved in packet transfer, while the remaining nodes were kept in sleeping node.

D. Kumar *et al.* [19] determined the weighted probability of each sensor node to elect a node as cluster head in WSN environment. The presence of variation in cluster count produced cluster with varying size. B. Elbhiri *et al.* [20] extended the work of DEEC by sending significant information of the sender to the base station and keeping the other nodes in a sleeping node. This protocol was application specific.

ElbhiriBrahim *et al.* [21] in their work selected advanced nodes as cluster head during the initial transmission, which decreased, the cluster head selection based on the probability. It also reduced the intra cluster transmission.

The existing works discussed above failed to deal with the real time problem of uncertainty in the selection of cluster heads and the optimal route when the information collected for processing was insufficient, inconsistent or incomplete.

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Thus, this proposal focuses mainly on handling such uncertainty by introducing the intuitionistic fuzzy decision matrix, which extends the degree of hesitation which is not handled by the fuzzy logic.

III. THE PROPOSED MODEL OF INTUITIONISTIC INSPIRED CLUSTER HEAD SELECTION FOR OPTIMIZED LOAD BALANCING TO INCREASE THE LIFE OF WIRELESS SENSOR NETWORKS

This work aims at handling the problem of the existence of uncertainty in the selection of cluster head in WSN. This work deploys two stages for overcoming the problem of optimal energy consumption by devising an adaptive Intuitionistic fuzzy based cluster head and optimal route selection. A key challenge raised is choosing an optimal cluster head in WSN, because the nodes are mobile in nature, and their attributes often change over time.

The Intuitionistic fuzzy logic uses three criteria for the selection of high energy cluster head by computing degree of membership (μ), degree of non-membership (ν) and degree of hesitation (π) for all the nodes' residual energy, distance and the number of neighbor nodes. The node with high degree of membership, low degree of non-membership and hesitation degree on the chosen cluster is declared as cluster head. After selecting the cluster head in clusters, the data to be transferred to the based station are collected from the cluster nodes and aggregated by the corresponding cluster heads. The second stage is to discover the shortest path to transfer these aggregated data packets to base station. For that, Intuitionistic Fuzzy Inference Engine is used for generating rules of selecting the optimal path which has a prolonged lifetime. The Overall framework of the proposed work is depicted in figure 1.

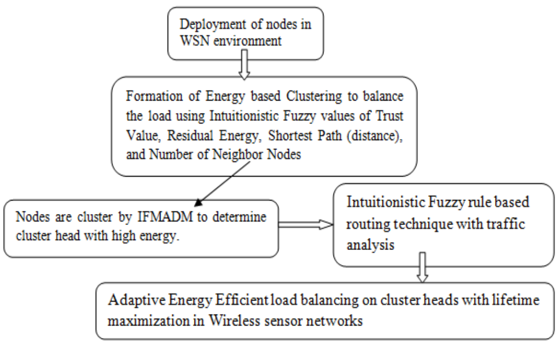

Figure 1: Proposed Adaptive Intuitionistic fuzzy Environment based Energy Consumption in WSN

Preamble of Intuitionistic Fuzzy Logic

Assume that X is a fixed set having at least one element in its set and falls under the interval [0, 1]. And it is denoted by I. A is an object which belongs to a set of intuitionistic fuzzy set [IFS] [23]and it is represented as

(1)

$$A=\{<x,\mu_A(x),\gamma_A(x)>|\,x\in X\}$$

Where, μ represents membership degree of a intuitionistic set and γ denotes non-membership degree of intuitionistic set. In this the intuitionistic fuzzy set A on a non-empty set X is represented with the membership degree $\mu_A(x)$ and the non-membership degree $\gamma_A(x)$ for each element in intuitionistic fuzzy set A which falls under the interval of [0, 1]. The sum of $\mu_A(x)$ and $\gamma_A(x)$ is always equals to 1 in fuzzy logic but it is always less than 1 in case of intuitionistic fuzzy logic due to the introduction of degree of hesitation denoted by $\pi_A(x)$ and it is defined as,

$$\pi_A(x) = 1 - \mu_A(x) - \nu_A(x) \qquad (2)$$

Adaptive Intuitionistic fuzzy logic based multi-attribute decision making in cluster head selection in WSN

Let us assume that in the adaptive intuitionistic fuzzy for making decisions using multi attributes to select the cluster head based on the characteristics of a node the following representations are made. In this, a set of instances is denoted as S, A as set of attributes, wt as weight and wt ϵ ψ which is the weight information. If the set ψ is contradictory then ψ is an empty set [25]. In such a situation the weighted information should be reconstructed until it is not paraconsistent. The weighted information can be assigned from the following term [25, 26] for selecting the cluster head to obtain a routing scheme, based on energy consumption.

A weak ranking

$$\mathbf{wt_i \geq wt_j}. \qquad \mathbf{(3)}$$

It means the weight of the attribute A_i is either greater than or equal to another attribute A_j.

Strict ranking,

$$\mathbf{wt_i - wt_j \geq \alpha_I}. \qquad \mathbf{(4)}$$

This represents that the attribute At_i is the best compared to the At_j and the attribute At_{ig} is the worst. It is clearly designed with their corresponding weight of the attributes repeated by

$$wt_i \geq wt_j \geq wt_k \quad \text{or}$$

$$wt_i - wt_j \geq \alpha_i \quad \& \quad wt_j - wt_k \geq \alpha_j. \qquad (5)$$

it means the weight of the attributes A_i exceeds that of A_j, where α_I & α_j are non-negative constancies A_j by at least α_I &the weight of the attributes A_j exceeds that of A_k by at least α_j.

A ranking of difference,

$$\{wt_i - wt_j \geq wt_k - wt_l\} \text{ for } j \neq k \neq l. \qquad (6)$$

It represents when the preference difference between wt_i &wt_j is greater than or equal to that between $wt_i \geq wt_j$. A ranking with multiple,

$$Wt_i \geq \alpha_I\, wt_j. \qquad (7)$$

It represents that the attribute A_j is the best and the attribute A_i is in the level greater than or equal to α_I ($0 \leq \alpha_I \leq 1$) relative to the level of the attribute A_j. It means the weight of the attribute A_i is greater than or equal to α_I times of that of the attribute A_j which is expressed an, $Wt_i \geq \alpha_i\, wt_j$. The interval form is

$$\alpha_i \leq wt_i \leq \alpha_i + \epsilon_I. \qquad (8)$$

It means that the crisp weight cannot be represented but value range can be obtained, then that type of weight is called interval weight. This is the most common form to describe the incomplete information about attribute weight, which can be provided directly provided by the experts.

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Let, $Z = (z_{ij})_{mxn}$ be an intuitionistic fuzzy decision matrix [25], Where, $Z_{ij} = \{ \mu_{ij}, \gamma_{ij}, \pi_{ij} \}$ is the triplet representation of an attribute's intuitionistic fuzzy value which satisfies the interval value lies between 0 to 1.

$$\mu_{ij} \in [0,1] , \gamma_{ij} \in [0,1] , \Pi_{ij} \in [0,1]$$

$$\mu_{ij} + \gamma_{ij} \leq 1 \qquad (9)$$

$$\Pi_{ij} = 1 - \mu_{ij} - \gamma_{ij} . \qquad (10)$$

Where i = 1, 2, 3, … m, where m represents number of attributes and j = 1, 2, 3, … n, and n represent the number of nodes. The Attribute A_i (i = 1,2,….m) undergoes normalization process when they are of mixed types, most probably the energy, distance, trust value and number of neighbor nodes are in different ranges of values which cannot be represented directly in form of IFS. So that, $Z = (z_{ij})_{mxn}$ is converted into intuitionistic fuzzy decision matrix $D = (d_{ij})_{mxn}$

$$d_{ij} = (\hat{\mu}_{ij} , \hat{\mu}_{ij} , \hat{\pi}_{ij})$$

$$= \begin{cases} Z_{ij} & benifit\_attribute\_A_i \\ (Z_{ij})^C & cost\_attribute\_A_i \end{cases} \quad \{ \qquad (11)$$

j=1,2,3,…..n}

$(Z_{IJ})^C$ it is the complement of the Z_{ij} such that

$$(d_{ij})^C = (\gamma_{ij} , \mu_{ij} ,\pi_{ij}) \qquad (12)$$

It is clearly mentioned as,

$$\pi_{ij} = 1 - \mu_{ij} - \gamma_{ij} = 1 - \hat{\mu}_{ij} - \hat{\gamma}_{ij} \qquad (13)$$

i=1,2,….m j=1,2,….n

in this every attribute d_{ij} must satisfy the criteria,

$$\mu_{ij} + \gamma_{ij} \leq 1 \qquad (14)$$

$$\mu_{ij} \leq 1 - \hat{\gamma}_{ij} \qquad (15)$$

It can be transformed the attribute value d_{ij} into the interval $d_{ij} = [\mu_{ij} , 1 - \gamma_{ij}]$. The expected value can be repeated as,

$$E(d_{ij}) = \frac{1}{2} (\hat{\mu}_{ij} + 1 - \hat{\gamma}_{ij}) \quad i = 1,2,\ldots..m \;\; j = 1,2,\ldots n$$

$$= \frac{1}{2} (\hat{\mu}_{ij} + \hat{\mu}_{ij} + \pi_{ij}) = \mu_{ij} + \frac{1}{2} \pi_{ij} \qquad (16)$$

The whole expected attribute value $E(d_j)$ respect to each and every substitute y_j by using additive weighted method,

$$E(d_j) = \sum_{i=1}^{m} wi \, E(d_{ij}) \qquad (17)$$

j=1,2,….n

$$= \sum_{i=1}^{m} wt_i \left(\hat{\mu}_{ij} + \frac{1}{2} \pi_{ij} \right)$$

$E(d_j)$ usually used to rank the analogous alternative y_j. The larger the overall expected attribute value $E(d_j)$, better the alternative y_i .

For an alternative $y_{11} \in Y$, such that E(rj) > E(rk) then y_k is called the dominated alternative [25].

Otherwise it is called a non-dominated alternative. y_k is dominated if and only if $J_k < 0$,

where,

$$J_k = \max \sum_{\substack{i=1 \\ i \neq k}}^{m} wt_i \left(\mu_{ik} + \frac{1}{2} \pi_{ik} \right) + \delta \leq 0 \qquad (18)$$

$$wt = (wt_1 , wt_2 ,\ldots..wt_n)^T \in \gamma \;\; wt_i \geq 0 \quad i = 1,2,\ldots..m,$$

$$\sum_{i=1}^{m} wt_i = 1. \qquad (19)$$

$\delta \rightarrow$ Is only an unconstrained auxiliary value.

In WSN, in order to discover the optimal load balancing, the cluster heads are to be cluster based on their characteristics. Four key characteristics namely residual energy, optimal path (i.e.) distance, trust value and the number of neighbor nodes are taken into account for selecting the most potential nodes to act as cluster heads. This is done by using interactive fuzzy multi attribute decision making system. Residual energy Att1, distance Att2, delay Att3, Bandwidth is Att4 and Queue size is Att5

Let us assume, the decision maker evaluates 5 cluster heads CHj (j=1,2,3,4,5) With respective to the key factor, Att_i = (i=1, 2, 3, 4, 5)

Using IFRs

$$r_{ij} = (\mu_{ij} , \gamma_{ij} ,\pi_{ij}) \qquad (20)$$

(i,j = 1,2,3,4,5)

Which are contained in the intuitionistic fuzzy matrix [26]

$$R = (r_{ij})_{5\times 5} \qquad (21)$$

And the largest information is expressed as,

$\psi = \{$ $wt, \leq 0.1$, $01 \leq wt_2 \leq 0.5$, $0.2 \leq wt_3 \leq 0.3$, $wt_4 \leq 0.1$, $wt_5 \leq 0.4$, wt_4, $wt_4 \leq wt_5$,

$$wt_i^t \geq 0, \quad i=1,2,3,4,5 \;\; \sum_{i=1}^{5} wt_t^i = 1 \;\; \} \qquad (22)$$

Since all the attributes A_i ,(i=1,2,3,4,5) are the benefit attributes then the attribute value in R need not be normalized.

Steps

1: compute the expected attribute value $E(r_{ij})$ of each and every attribute value r_{ij} in R by using equation.

$$E(r_{ij}) = \mu_{ij} + \frac{1}{2} \pi_{ij} \qquad (23) \quad i = 1,2,3,\ldots.m \quad j = 1,2,3,\ldots.n$$

	CH_1	CH_2	CH_3	CH4	CH5
A1	(0.4,0.3,0.3)	(0.3,0.6,0.1)	(0.5,0.2,0.3)	(0.3,0.5,0.2)	(0.3,0.4,0.3)
A2	(0.4.0.5,0.1)	(0.2,0.5,0.3)	(0.7,0.1,0.2)	(0.6,0.2,0.2)	(0.2,0.6,0.2)
A3	(0.7,0.1,0.2)	(0.6,0.3,0.1)	(0.4,0.4,0.2)	(0.3,0.6,0.1)	(0.5,0.4,0.1)
A4	(0.8,0.1,0.1)	(0.3,0.5,0.2)	(0.5,0.4,0.1)	(0.4,0.5,0.1)	(0.7,0.2,0.1)
A5	(0.5,0.2,0.3)	(0.4,0.4,0.2)	(0.3,0.2,0.5)	(0.5,0.1,0.4)	(0.8,0.1,0.1)

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Example: $E(r_{12}) = \mu_{12} + \frac{1}{2}\pi_{12} = .4 + \frac{1}{2} \times .3 = .4 + .5 \times .3 = .4 + .15 = 0.55$

$\in (\gamma_{11}) = 0.55 \in (\gamma_{13}) = 0.65 \in (\gamma_{15}) = 0.45 \in (\gamma_{22}) = 0.35 \in (\gamma_{24}) = 0.70 \in (\gamma_{31}) = 0.80 \in (\gamma_{33}) = 0.50 \in (\gamma_{35}) = 1$

$\in (\gamma_{12}) = 0.35 \in (\gamma 14) = 0.40 \in (\gamma_{21}) = 0.45 \in (\gamma_{23}) = 0.80 \in(\gamma_{25}) = 0.30 \in (\gamma_{32}) = 0.65 \in (\gamma_{34}) = 0.35 \in (\gamma_{41}) = 0.85$

$\in (\gamma_{42}) = 0.40 \in (\gamma_{44}) = 0.45 \in (\gamma_{51}) = 0.65 \in (\gamma_{53}) = 0.55 \in (\gamma_{55}) = 0.85 \in (\gamma_{43}) = 0.50 \in (\gamma_{45}) = 0.75 \in(\gamma_{52}) = 0.50$

$\in (\gamma_{54}) = 0.70.$

and then get the overall expected attribute value $\in(r_j)$ according to each cluster head CH_j ,

$$E(r_j) = \sum_{i=1}^{m} wt_i \; E(r_{ij}) \qquad j=1,2,3,\ldots n \qquad (24)$$

		1	2	3	4	5
$E(r_{ij}) =$	1	10.55	0.35	0.65	0.40	0.45
	2	0.45	0.35	0.80	0.70	0.30
	3	0.80	0.65	0.50	0.35	1
	4	0.85	0.40	0.50	0.45	0.75
	5	0.65	0.50	0.55	0.70	0.85

$E(r_1) = 0.55\, wt_1 + 0.45\, wt_2 + 0.80\, wt_3 + 0.85\, wt_4 + 0.65\, wt_5$

$E(r_2) = 0.35\, wt_1 + 0.35\, wt_2 + 0.65\, wt_3 + 0.40\, wt_4 + 0.50\, wt_5$

$E(r_3) = 0.65\, wt_1 + 0.80\, wt_2 + 0.50\, wt_3 + 0.50\, wt_4 + 0.55\, wt_5$

$E(r_4) = 0.40\, wt_1 + 0.70\, wt_2 + 0.35\, wt_3 + 0.45\, wt_4 + 0.70\, wt_5$

$E(r_5) = 0.45\, wt_1 + 0.30\, wt_2 + 1\, wt_3 + 0.75\, wt_4 + 0.85\, wt_5$

In order to identify whether the cluster head CH_1 is a dominated alternative or not, by establishing the Linear programming model [26] in cluster head selection is as follows:

$J_1 = \max (0.55\, wt_1 + 0.45\, wt_2 + 0.80\, wt_3 + 0.85\, wt_4 + 0.65\, wt_5 + \delta_1 - \delta_2)$

St $\quad 0.35\, wt_1 + 0.35\, wt_2 + 0.65\, wt_3 + 0.40\, wt_4 + 0.50\, wt_5 + \delta_1 - \delta_2 \leq 0$

$0.65\, wt_1 + 0.80\, wt_2 + 0.50\, wt{=} + 0.50\, wt_4 + 0.55\, wt_5 \; \delta_1 - \delta_2 \leq 0$

$0.40\, wt_1 + 0.70\, wt_2 + 0.35\, wt{=} + 0.45\, wt_4 + 0.70\, wt_5 \; \delta_1 - \delta_2 \leq 0$

$0.45\, wt_1 + 0.30\, wt_2 + 0.1\, wt{=} + 0.75\, wt_4 + 0.85\, wt_5 \; \delta_1 - \delta_2 \leq 0$

$\delta_1 \geq 0,\ \delta_2 \geq 0, w_i \geq 0, \quad i = 1,2,3,4,5$

$$\sum_{i=1}^{5} wt_i = 1$$

$wt_1 \leq 0.1$, $0.1 \leq wt_2 \leq 0.5$, $0.2 \leq wt_3 \leq 0.3$, $wt_4 \leq 0.1$, $wt_5 \leq 0.4$, $wt_4 \leq wt_5$, $\delta = 0.0000$, $\delta_2 = 0.6140$

$wt_1 = 0.1000$, $wt_2 = 0.4800$, $wt_3 = 2200$, $wt_4 = 0.1000$, $wt_5 = 0.1000$

$J_1 = \max (0.55 \times 0.1 + 0.45 \times 0.48 + 0.80 \times 0.22 + 0.85 \times 0.1 + 0.65 \times 0.1 + (0.0 - 0.61)$

$= 0.055 + 0.216 + 0.176 + 0.85 + 0.65 - 0.61 = -0.013$

Since CH_1 is formed to be negative value, it is discovered that the node which is designated as CH_1 is the dominated cluster head in the $cluster_1$.

Likewise, for the cluster head selection in second cluster CH2

$\delta = 0.0000$ $\quad \delta_2 = 0.6125$ $\quad Wt_1 = 0.1000$
$wt_2 = 0.3129$ $\quad Wt_3 = 0.2540$ $\quad wt_4 = 0.0020$
$Wt_5 = 0.3010$

J2 = 0.35 x 0.1000+ 0.35 x 0.3129 + 0.65 x.2540 + 0.40 x 0.0020 + 0.50 x 0.3010 + 0 -0.6125

J2= - 0.151585

For the cluster head selection (CH3) in third cluster

$\delta = 0.0000$ $\quad \delta_2 = 0.5902$ $\quad Wt_1 = 0.0960$
$wt_2 = 0.3145$ $\quad Wt_3 = 0.2013$ $\quad wt_4 = 0.0001$
$Wt_5 = 0.3228$

J3 = 0.65 x 0.0960+ 0.80 x 0.3145 + 0.50 x.2013 + 0.50 x 0.0001 + 0.55 x 0.3228 + 0-0.3228

J3 = 0.0036

In cluster 3, the node which is elected as cluster head holds the positive value of 0.0036 which represents that the chosen node is not a dominated node so that another prominent node has to be selected as CH3.

For the cluster head selection (CH4) in fourth cluster

$\delta = 0.0000$ $\quad \delta_2 = 0.6117$ $\quad Wt_1 = 0.0723$
$wt_2 = 0.1120$ $\quad Wt_3 = 0.2985$ $\quad wt_4 = 0.1000$
$Wt_5 = 0.3999$

J4 = 0.40 x 0.0723+0.70x0.1120+0.35 x 0.2985+ 0.45 x 0.1000 + .70 x 0.3999 + 0 -0.6117

J4= - 0.0749

In cluster 4, the node which is elected as cluster head holds the negative value of -0.0749 which represents that the chosen node is a more prominent and dominated node CH4.

For the cluster head selection (CH5) in fifth cluster

$\delta = 0.0000$ $\quad \delta_2 = 0.6033$ $\quad Wt_1 = 0.0001$
$wt_2 = 0.4902$ $\quad Wt_3 = 0.2990$ $\quad wt_4 = 0.0718$
$Wt_5 = 0.1192$

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J5 = 0.45 x 0.0001+ 0.30 x 0.4902 + 1 x.2990 + 0.75 x 0.0718 + 0.85 x 0.1192 + 0 -0.6033

J5= - 0.0080

In cluster 5 the node which is elected as cluster head holds the negative value of -0.0080 hence due to its dominant feature the chosen node is CH5 to prominently transfer the aggregated data packets.

Intuitionistic Fuzzy based Optimal Route Selection

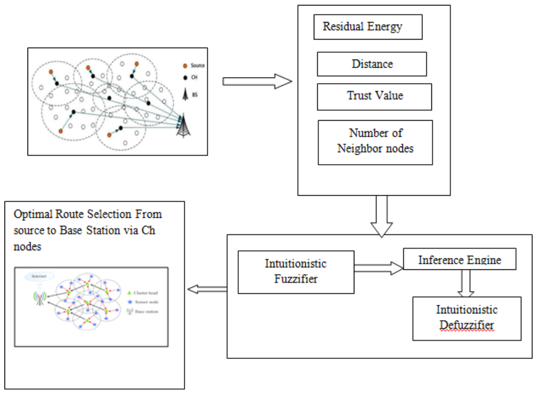

Figure 2: Overall working model of route selection process

After the selection of potential cluster heads based on interactive Intuitionistic fuzzy multiattribute decision making system the optimal route selection from the source to the base station is selected using Intuitionistic fuzzy inference-based rule selection strategy. **Figure 2** depicts an overall working model of the route selection process. The cluster head and intermediate cluster heads, information like residual energy, distance and truth value and the number of neighbor nodes are considered for inferring the rule, and the given input is represented in the format of Intuitionistic fuzzy value namely membership, non-membership and hesitation degrees. The triangular representation [22] of Intuitionistic fuzzy is shown in figure 3

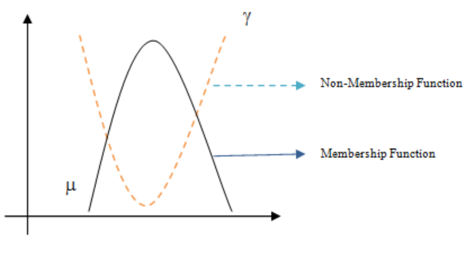

Figure 3: Intuitionistic Fuzzy member ship and non-membership Function Representation

The Intuitionistic fuzzified values are processed by the inference engine, in terms of membership, non-membership and hesitation degree of each input attribute, and the rules are framed using simple IF-then rules. These inputs produce the output about the reliability of the path, stating whether the chosen path is suitable under the five different criteria namely energy consumption, distance, delay, bandwidth and queue size. This output is also used, for inferring the rules from the implication of logical operators namely AND, OR, NOT in the form of intuitionistic fuzzy logical operator using MIN-MAX strategy. The portions 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 IFS implication rules such as MIN-MAX [18] 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 in to the finals intuitionistic fuzzy solution space.

Sample: Intuitionistic Fuzzy Rule Generated for Optimized Route Selection

- If $CH_i(att_1)$ is low and $CH_i(att_2)$ is low and $CH_i(att_3)$ is medium and $CH_i(att_4)$ is high then the cost is high.
- If $CH_i(att_1)$ is high and $CH_i(att_2)$ is high and $CH_i(att_3)$ is low and $CH_i(att_4)$ is high then the cost is low.
- If $CH_i(att_1)$ is medium and $CH_i(att_2)$ is medium and $CH_i(att_3)$ is medium and $CH_i(att_4)$ is high then the cost is indeterministic.

Like the above 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.

Algorithm: Intuitionistic Fuzzy Environment based Energy Consumption in Wireless Sensor Networks

Initialize the simulation network using the parameter setting as mentioned in the table

Step 1: Let Z be the intuitionistic fuzzy decision matrix where Z_{ij} represents $(t_{ij}, f_{ij}, \pi_{ij})$ attribute values. Att represents four parameters of each sensor node (residual energy, distance, trust value and number of neighboring nodes), the weight of each attribute Att_i is represented using *W*.

Step 2: The Matrix B is transformed into the normalized intuitionistic fuzzy decision matrix D = $(d_{ij})_{m\times n}$ using the equation.

Step 3: Compute the expected attribute value $E(d_{ij})$ of each attribute value r_{ij} in R and then get the overall expected attribute value $E(d_j)$ corresponding to each alternative y_j by using the simple additive weighted method.

Step 4: Identify whether the alternative y_j is the dominated alternative or not and omit the dominated alternatives, and then get set *Y*, whose elements are the non-dominated ones. If the decision suggests that the alternative $y_k \in Y$ be preferred to any other alternatives in *Y* or the alternative y_k is only one left in *Y*, then the alternative y_k is the optimal one, go to Step 5; Otherwise, go to Step 4.

Step 5: Update the new weight information to the set $\boldsymbol{\psi}$, if the updated information contradicts the weight information in $\boldsymbol{\psi}$, then return it to the decision maker for re-evaluation, and go to Step 3.

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Step 6: From the selected Cluster head the intuitionistic fuzzy inference the engine-based rule is generated.

Step 7: The resultant rules aids in selecting the optimal route which increased the network lifetime.

Step 8: End.

IV. SIMULATION RESULTS

The simulation has been accomplished using matlab Software by deploying sensor nodes in a random 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 information to the base station. The preliminary number of clusters is predetermined by choosing potential value and changes continuously with the node 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 located at the center of the field.

Table 1: Simulation Parameter

Parameter	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/m2	Energy consumed by the amplifier to be transmitted at a short distance
ε_{mp}	0.0013 pJ/bit/m4	Energy consumed 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

The Figure 4 shows the Initial Setup of the WSN using NS2 and the figure 5 shows the resultant output after finding the optimal cluster head and path selection from the cluster heads to the base station.

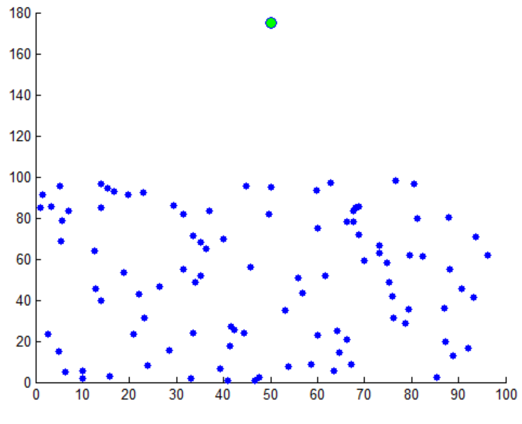


Figure 4: Initial Setup of the network

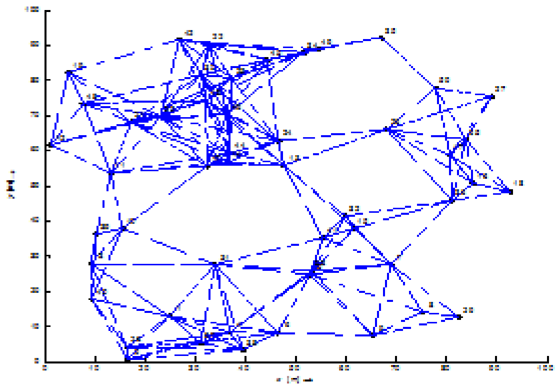
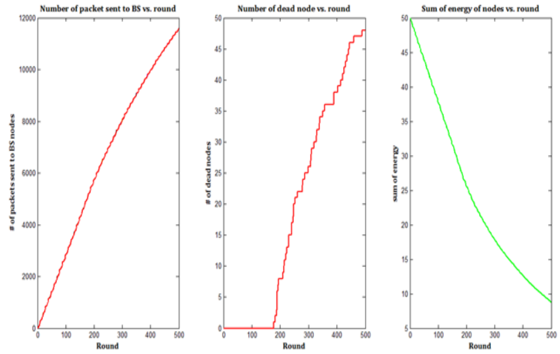


Figure 5: Node Clustered using cluster head and Base station

The output model of the proposed Adaptive Intuitionistic Fuzzy Multi Attribute Based Decision Making for cluster head selection with input parameters residual energy, distance, trust value and number of neighbor nodes determines the most prominent cluster head which has the high quality of degree of the degree of membership, non-membership and hesitation degree on the three criteria. During each round of clustering the cluster heads are selected based on those three characteristics, and after applying intuitionistic multi-attribute decision making, the rules are applied to determine the non-dominant node and elect it as cluster head. The size of the cluster varies in each round because the cluster with a smaller size is merged with the bigger



a) b) c)

Figure 6 (a-f) depicts the outcome of the proposed AIFMADMCH selection method with the varying rounds ranging from 0 to 250. After performing a few rounds the output is shown through figures 6(a,b,c), and at the end of utmost rounds the results are shown in figure 6(d,e,f). The number of packets passed to the base station keeps on growing due to the selection of prominent cluster head as shown in figure (a, d), which has the high stability of lifetime by showing low number of dead nodes. This is due to the fact that, the hesitation degree is considered as an important constraint for unknown situation of boundary nodes, which are present in the cluster, and are also given importance. The energy consumption in figure (b, e) is considerably better.

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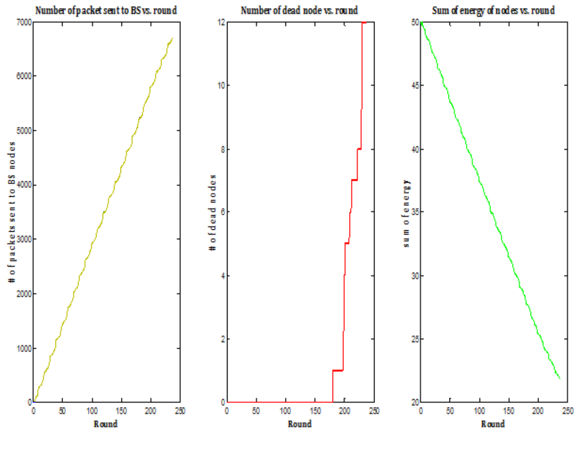
The figures (c, f), show that in each round, due to the selection of cluster head with high degree of membership on four different parameters namely residual energy, distance, trust value and number of neighbor nodes with its corresponding non-membership and hesitation values are low, and the chosen cluster head wins the round and achieves the goal of this proposed scheme



(d) (e) (f)

Figure 6: (a- f) Outcome of efficient network lifetime with link stability and energy Consumed in each round by AIFMADMCH

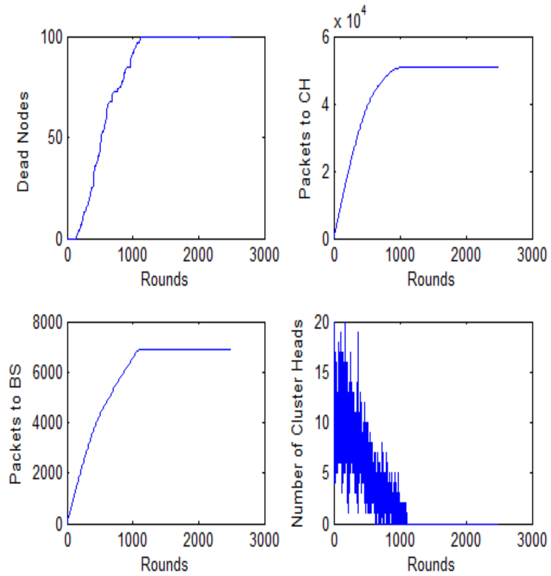


Figure 7: The performance result of the Intuitionistic fuzzy based decision making

Figure 7 shows the performance result of the Intuitionistic fuzzy based multiattribute decision making based on the five key factors of each sensor node with cluster round ranges from 0 to 3000. Each attribute's (energy consumption, trust value, distance and number of neighboring nodes) μ (degree of membership), γ (degree of non-membership) and π (degree of hesitation) are identified by normalizing their value and determining their intuitionistic fuzzification values calculated by

$$\mu_A(x)=\begin{cases} 0 & (x\le a)\\ \dfrac{x-a}{b-a}-\in & a<x\le b\\ \dfrac{c-x}{c-b}-\in & b\le x<c\\ 0 & x\ge c \end{cases}$$

$$\nu_A(x)=\begin{cases} 1-\in & (x\le a)\\ 1-(\dfrac{x-a}{b-a}) & a<x\le b\\ 1-(\dfrac{c-x}{c-b}) & b\le x<c\\ 1-\in & x\ge c \end{cases}$$

The trif is specified by three parameters as shown in the figure a lower limit a, an upper limit c, and a value b, where a ≤ b ≤ c. The precise appearance of the function is determined by the choice of the parameters a, b, c which in turn forms a triangle. In this a and c locate the feet of the triangle and the parameter b locates the peak.

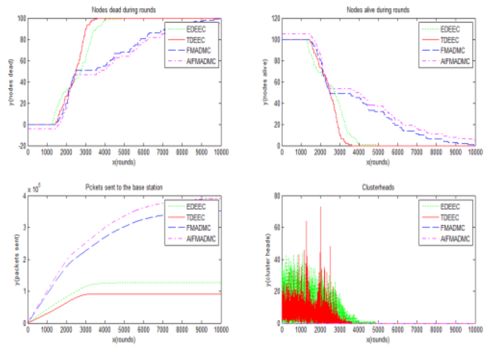


Figure 8: Performance Evaluation of proposed work with other algorithms for cluster head selection on the basis of packets delivered, node life time, number of nodes dead and cluster head selected at each round

It is observed that the performance of the proposed AIFMADMC provides more promising result in all the comparisons. The packet delivery towards the base station is high because the lifetime of the cluster head is maintained consistently. This is due to the selection of such optimal cluster head with five parameters intuitionistic values and obtaining the expected value and determining the benefit attributes and the cost attributes using intuitionistic fuzzy decision- making matrix. The corresponding alternatives are identified and the non-dominated sensor node is selected as the cluster head in each round. The sensor nodes send their data packets to the cluster head based on residual energy, the number of neighbors, trust value and distance from base station respectively. The performance of the proposed AIFMADMC increase with 20% of the existing fuzzy based decision-making system by choosing the optimal path through the intuitionistic fuzzy inference system.

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V. CONCLUSION

This paper addresses the issues in optimal energy consumption in WSN when the information for selecting the cluster head is incomplete or imprecise to take a proper decision. The avoidance of such factors leads to the increase in false selection of optimal cluster head which degrades the overall performance of the network. Specifically, in this work we have designed an optimal energy consumption framework using the Intuitionistic fuzzy approach for both cluster head selection and discovering route between cluster heads and base station. This is achieved by selecting the cluster heads, based on energy consumption during each round, extension of network lifetime by eliminating the dead nodes as cluster head, finding the trustworthiness of each node and the stabilized path link using the intuitionistic fuzzy inference-based rule generation system. The proposed AIFMADMC suits well in emergency cases of real time applications by efficiently handling the uncertainty in cluster head selection and optimal route selection compared with EDEEC, TDEEC and Fuzzy based Decision-making system. This is due to the fact that the AIFMADMC works well in the case of indeterminacy, while others are negotiated based on this situation. The expected value, the attribute weight selection strategies and the alternative node selection greatly aid in deciding the hesitation degree value for cluster head selection, thereby increasing the performance of AIFMADMC.

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