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Genetics Based Compact Fuzzy System for Visual Sensor Network

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Abstract: As a component of Wireless Sensor Network (WSN), Visual-WSN (VWSN) utilizes cameras to obtain relevant data including visual recordings and static images. Data from the camera is sent to energy efficient sink to extract key-information out of it. VWSN applications range from health care monitoring to military surveillance. In a network with VWSN, there are multiple challenges to move high volume data from a source location to a target and the key challenges include energy, memory and I/O resources. In this case, Mobile Sinks (MS) can be employed for data collection which not only collects information from particular chosen nodes called Cluster Head (CH), it also collects data from nearby nodes as well. The innovation of our work is to intelligently decide on a particular node as CH whose selection criteria would directly have an impact on QoS parameters of the system. However, making an appropriate choice during CH selection is a daunting task as the dynamic and mobile nature of MSs has to be taken into account. We propose Genetic Machine Learning based Fuzzy system for clustering which has the potential to simulate human cognitive behavior to observe, learn and understand things from manual perspective. Proposed architecture is designed based on Mamdani's fuzzy model. Following parameters are derived based on the model residual energy, node centrality, distance between the sink and current position, node centrality, node density, node history, and mobility of sink as input variables for decision making in CH selection. The inputs received have a direct impact on the Fuzzy logic rules mechanism which in turn affects the accuracy of VWSN. The proposed work creates a mechanism to learn the fuzzy rules using Genetic Algorithm (GA) and to optimize the fuzzy rules base in order to eliminate irrelevant and repetitive rules. Genetic algorithm-based machine learning optimizes the interpretability aspect of fuzzy system. Simulation results are obtained using MATLAB. The result shows that the classification accuracy increase along with minimizing fuzzy rules count and thus it can be inferred that the suggested methodology has a better protracted lifetime in contrast with Low Energy Adaptive Clustering Hierarchy (LEACH) and LEACH-Expected Residual Energy (LEACH-ERE).

Keywords: Visual sensor network; fuzzy system; genetic based machine learning; mobile sink; efficient energy; life of network

1 Introduction

Visual-Sensor-Networks (VSNs) are dimensionally dispersed low-power sensors fitted with cameras for monitoring and recording multimedia information. VSN has contributed towards enhancing our lives better through its diverse application deployments such as threat detection, remote healthcare monitoring of disabled and elderly, espionage, environmental, disaster management, agricultural and industrial services. Visual data are collected from scattered camera fitted sensors, processed collectively, and sent to the sink. In comparison with WSNs, which performs the function of sensing and transmitting data acquired from its environment, VWSNs deals with multimedia data and can be considered as an improvised extended version of WSNs whose data processing ability of VWSN is un paralleled. Comparing to other nodes, the probability of, rate at which the energy drains is more for the nodes which are nearer to the sink node because of data traffic towards static sink; this scenario is called energy-hole or it is also called as hot-spot issue [1] as shown in Fig. 1. A mobile sink is deployed to overcome this situation. Load across the sensors need to be equally distributed to effectively use the energy across the network. In-order to achieve energy efficiency, the location of hotspot is change dynamically with respect to the location of sink [2]. The mobile sink enters a Region of Interest (ROI) and collects all information to be transmitted from surrounding nodes. Main advantage of mobile sink is it is used to lessen the total hops required to transmit data by sensor nodes. Dispatcher unloads the data to sink when it is nearer to its location. Network infrastructure need to be sophisticated in-order for this design to work seamlessly. Any problem with respect to the mobile sink or to any internal node need to be monitored and published dynamically [3]. The energy aware algorithms designed so far has taken into account many desirable characteristics [4]. Among them, partitioning the network (Clustering) for data transmission has portrayed to be efficient in enhancing the network lifetime and performance. In clustering mechanism based VWSN, the whole network is partitioned into clusters where every sensor communicates with its associated cluster head (CH). Each CH is accountable for assimilation of information collected from its members and transmitting them straight or routing through other CHs to communicate with mobile sink node [5]. To minimize power consumption of CHs, MS must be in motion to gather information from CH, traversing through a short optimized energy aware route of transmission.

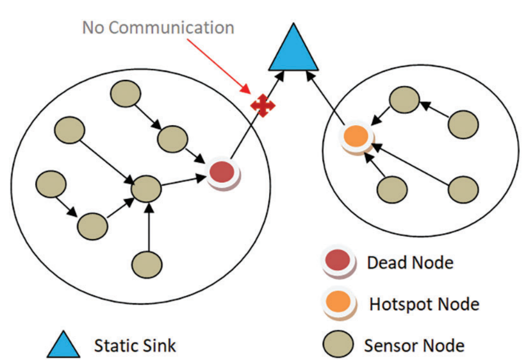

Figure 1: An illustration of the typical clustered network with energy-hole problem

Our proposed study presented here uses genetic machine learning model to effectively select a cluster head by considering energy awareness strategies. Hybrid Machine Learning (ML) model utilizes the key advantages in genetic algorithm and also fuzzy systems. Key attributes that determine the cluster head are

(a) rule based fuzzy inference engine, (b) mobility, (c) node density, (d) distance of node and residual energy. We further make use of genetic algorithm based Machine Learning in a system based on fuzzy model, which assists in selecting right node as cluster head; by this way the energy consumed by the network is efficient. In this paper, an innovative ML model using fuzzy-logic, Genetic-Algorithm (GA) is used, where Mamdani's fuzzy logic is adopted which makes use of various node attributes such as mobility, centrality, energy, distance, density, history to decide on CH. Above parameters are applied on all the nodes in the network to select a cluster head. Fuzzification process is executed to map the input information into corresponding variable. The fuzzy inference rule base has all necessary information which specifies the required performance is depicted as conventions. Pre-designed rules based on fuzzy logic will be spread out to arrive at required interpretations and decisions by the inference engine. Defuzzification which has its functioning exactly opposite to fuzzification outputs the actual input data that are used for subsequent operations. Chances of a node to be designated as cluster-head is calculated by means of designing a compact inference rule oriented fuzzy system which adopts the Genetic based Machine learning method and Mamdani's fuzzy logic to optimize the performance of VWSN. This scheme can be adopted to many application areas like surveillance, health care, automatic check for business readiness etc.

Remaining sections in this study is organized as: Section 2 focuses on existing literatures that motivated us towards taking up this research followed by the suggested system model along with network and energy dissipation models in Section 3. Architecture of our hybrid model is discussed in detail in Section 4 whose prototype is illustrated in Section 5. Performance aspects of the hybrid scheme of this study are discussed in Section 6 and Section 7 enlist the prominent details that have been the core functionality pertaining to our research.

2 Related Work

Agrawal et al. [6] created a Fuzzy Logic T-1 system with dual effects. Here, the previous result concludes the message transfer radius while the latter determines whether the node will be CH or not. Thangaramya et al. [7] proposed a unified approach which accompanied an exceptionally complicated method. Predominantly, to find out the optimum CH, Convolution Neural Network (CNN) was used. Shivappa et al. [8] suggested a way in which the Base Station (BS) uses AI as Fuzzy Cognitive Map to characterize to characterize the optimum central location of all clusters. Mohammad Alia [9] aims to enhance the rate at which data is transmitted through an optimal selection and allocation procedure where the cluster count and its allocation are automatically performed by harmony search oriented integrated approach. A beta-function is derived using factors like location, residual energy and its position from BS. Mehra et al. [10] assigns every sink node a probability factor which is calculated by sending the distance from base station as an input parameter to gamma function. It's a distributive scheme that employs fuzzy logic to arrive upon a suitable option for CH. In [11] the CH selection is carried out on the basis of two significant strategies namely its location and energy. If a node has mid location and possesses maximum energy, it becomes CH for life; else the node is designated as transient CH. Mirzaie et al. [12] is one of the frequently used clustering algorithms in environment where the sensors are diverse. This scheme makes use of a pre determined threshold to keep away from redundant clustering after a certain number of rounds. The analysis criteria are based on residual energy, dead nodes, First Node Dies (FND), Half Node Dies (HND), and Last Node Dies (LND). Energy-aware distributed dynamic Clustering Protocol using Fuzzy-logic (ECPF) takes into account degree and centrality factors of nodes as desirable inputs for fuzzy logic-based calculation to generate output for CH selection. Mazumdar et al. [13] proposes a routing protocol which uses an asymmetrical clustering means to fix the challenges due to WSN-hot-spot. This is achieved by minimizing cluster size in vicinity to base station. Enhanced clustering algorithm based on fuzzy Logic (ECAFL) protocol [14] used for routing is aimed to progress the performance of the Fuzzy Logic based Clustering Algorithm (CAFL) [15] algorithm by making way for greater node density. It utilizes sink distance, residual energy, and node density attributes as deciding parameters to evaluate ranks while selecting the appropriate CH. Ayati et al. [16] proposes fuzzy logic system, within which the nodes parameters are used. Parameters used in primary level are centrality, residual-energy, as well as secondary level parameters like communication and distance from BS are considered. Final decision is based on DOS-attack scenarios and lifetime. Depending upon such critical parameters, effective CH is chosen among various CHs. Super Cluster Head election using Fuzzy logic in Three Levels (SCHFTL) prevents the overload, failure and retransmission of information along with prolonging the network life. Another protocol Fuzzy-based Unequal Clustering Algorithm (FUCA) [17] is for CH selection involves disproportionate clustering making use of fuzzy logic phenomenon. In [18] Marwa Mamdouh et al, certain ML techniques were found to be constructive when applied in WSNs for conservation of energy and reliable transmission. In the Supervised Learning method of ML, the model is trained based on learning function which learns from known inputs and desired outcomes. This learning helps in predicting outputs in case of new inputs. In [19] Gaussian Naive Bayes classifier is designed on probabilistic Bayes' theorem which does not associate classes. In [20] a routing process is suggested where routing is performed through online clustering which also maintains a history of clustering information that can be referred in future. In [21] an energy efficient routing protocol for fishermen is proposed which uses Threshold-Optimized Depth Based Routing (iAMCTD) to identify border of their country while fishing. The technique follows these strategies: minimizing of spaces between nodes in cluster, reducing the space between candidate CH nodes and sink nodes, and online appropriate energy allocation mechanism to guarantee uniform distribution of energy among stake holders in all clusters. To optimize the logic of classifier systems, many heuristic approaches such as Particle Swarm Optimization (PSO), simulated annealing and GA has been adopted [22–24].

Summary: These approaches act as pedagogy algorithms, to improve classification accuracy by optimizing or constructing fuzzy rules base and minimize fuzzy rules count. Existing cluster-based protocols are primarily concerned with optimal cluster formation, selection of best CH, and uniform power distribution among sensor nodes. Relatively lesser researches have contributed towards identification of solutions to prevent Cluster Head nodes from dying prematurely.

Yet, they experience certain constraints such as:

- The parameters chosen for fuzzy set could have been accurate enough to produce the desired results.
- Systematic incorporated approach is required to enhance the cluster development process along with fuzzy controller managed updates.
- The current strategies must improvise to accommodate several prerequisites of VWSN in order to be deployed in real world application environments with respect to power consumption, resource requirements along with its dynamic and mobility oriented aspects.
- Accuracy of the application is at stake when the selected input data has wide variance with respect to a fuzzy rule.
- Any fuzzy rule doesn't have a centralized controller due to the inherent nature of the design.

The aforementioned shortcomings can be dealt with effectively through our suggested Energy-aware Genetic Algorithm-based compact fuzzy logic system for clustering in visual sensor networks.

Problem Statement: Network lifetime can be prolonged by choosing an appropriate set of parameters for Fuzzy Inference System and generate cluster update cycle through rule base reduction by means of GA-based ML approach to accomplish the necessary interpretability. Energy consumption based objective is achieved through chance identification of CH nodes which promotes enhanced and effective clustering.

3 System Architecture

3.1 Network Design

Following are the high level assumptions regarding network architecture:

- To effectively monitor destined target, participating sensors are dispersed across network.
- It is assumed that, once deployed the nodes remain static.
- Nodes have the ability to modify their transmit power using power control.
- All of the nodes possess equal energy levels and remain static throughout.
- Base Stations are mobile, and their position in VSN changes to a pre-planned path.
- There are no energy constraints for the mobile sink.
- Throughout the communication, there is no barrier between a transmitter and a receiver.

3.2 Energy Model

An innovative energy efficient model has been referred from [25]. The suggested approach implements the required intra communication between CHs and MS, as well as the inter communication among various CHs. The radio electronics are powered by the energy dispelled by the transmitter and receiver. Free-space data transfer scheme (Δ^2 power lose) and multipath scheme (Δ^4 energy lose) are actively deployed to perform the necessary operations. Significant factor considered is the distance (Δ) between sending and receiving node. If the condition ($\Delta < \Delta_0$) is met, we use the free space approach else multi path approach is selected. Eq. (1) depicts energy toil when transmitting parts if k bits of data are transmitted over a distance Δ. Eq. (2) depicts the amount of energy dissipated in this process. There is a threshold Δ_0 *in* Eq. (3).

$$\mathrm{E_{tx}}(\mathrm{k},\ \Delta) = \begin{cases} k * \mathrm{E_{elec}} + k * \varepsilon_{\ \mathrm{fs}} * \Delta^2, & \Delta \le 0 \\ k * \mathrm{E_{elec}} + k * \varepsilon_{\ \mathrm{mp}} * \Delta^4, & \Delta \ge 0 \end{cases} \tag{1}$$

$$\mathrm{E_{rx}}\ (\mathrm{k}, \Delta) = \mathrm{k} * \mathrm{E_{elec}} \tag{2}$$

$$\Delta_0 = \sqrt{\frac{\varepsilon_{\mathrm{fs}}}{\varepsilon_{\mathrm{mp}}}} \tag{3}$$

4 Proposed Approach

An innovative energy aware WVSN based on GA and optimized Fuzzy system for CH selection has been proposed in this paper. The objective of our work is to put forward an effective solution for CH selection to enable efficient data assimilation between CH and its member MS. All CHs confirm the identification of the sinks before imparting visible information. Verification ensures secure transactions. In the case of a connection among two nodes, data verification can benefit all the way through a message verification code blended with a commonplace undisclosed key. MS starts its journey from a predetermined position and moves along a designated path. MS are grouped into clusters, and CHs are chosen based on proposed approach. Each node employs a Mamdani's fuzzy system to make a decision regarding the selection of the CH node. To select the CH, fuzzy logic is employed through which greater precision and accuracy is ensured. The accuracy is achieved by carefully selecting the input parameters to the fuzzy system. In terms of network traffic stability, reduce delay time, and increase energy consumption, BS mobility is more reliable. The fuzzy system is optimized using Machine Learning based on GA. The considered input variables guarantee the accuracy in decision making. With the increase in fuzzy rules, there would be a corresponding increase in computational complexity, resulting in reduced efficiency and robustness of the generated outcome. Furthermore, the subsequent interpretation and analysis gets affected in the due process. In proposed method the Genetic based Machine Learning's Michigan approach is a key component assisting in optimizing fuzzy logic repository. Key input attributes and its associated hierarchical rules have crucial role in defining the core operating model. In our technique, 6 parameters are utilized for every node (denoted as 'n') for a given set of rounds denoted as 't'. List of input parameters are discussed in detail in rest of our study.

4.1 Candidate Node–Left over Energy

Significant attribute contributing towards overall efficiency of VWSN is residual energy and it is mainly due to the constraints with respect to less energy availability of batteries used in sensors. Energy within the sensory–nodes gets drained while selecting a cluster head. Power saved within the cluster-head should be sufficient enough to perform gathering and assimilation in accordance with certain predetermined strategies before routing it to the next CH or MS. As a result, energy/power level of a node is one of the critical parameters in selecting head of the cluster; power level of a CH should be more than any other node in the clusters. Eq. (4) denotes the residual energy of node.

$$E_{residual} = E_{initial} - E_{consumed} \tag{4}$$

where, $E_{residual}$ is residual energy, $E_{initial}$ is original energy, $E_{consumed}$ is energy consumed during the operation.

4.2 Distances between Sink and Candidate

Distance to Sink (DS)-Unit measurement that represents distance between current location and sink. As the distance between transmitter and sink increases, so does the power consumed by data transmission. Value of DS need to be reduced in-order to save energy and improve the lifetime. Following Eq. (5) calculates Euclidean distance from n to MS.

$$d(n, MS) = \sqrt{(x_n - x_{MS})^2 + (y_n - y_{MS})^2} \tag{5}$$

Coordinate value is computed using $(x_n - x_{MS})$ and $(y_n - y_{MS})$. Earlier formula is for current node and later is for MS.

4.3 Node Density

The count of single hop neighboring nodes within node's communication radius is referred to as node density. It is also important to consider the density around the potential CH, because more cluster members result in more energy dissipation by the CH during communication and data transfer process. In terms of node density, the overhead of the CH is also considered because it determines the cost of intra-cluster communication. This parameter is vital in selecting the head of cluster, because density of node is directly proportional to the lifetime and it also decreases the distances between clusters, which is denoted in Eq. (6):

$$\text{Node Density} = \sum_{\substack{i=1,\\ i \neq n}}^{N} NDensity(n, i) | i \in X \tag{6}$$

$N \rightarrow$ *Count of active sensory node.*

$NDensity \rightarrow$ *Function to find count of surrounding active nodes.*

4.4 Node History

The node's history is determined by previous cycles where a node was performing cluster head operation. Previous histories of CH nominations are stored in a temporary buffer maintained within the node. Threshold should be maintained which will track the occurrences of a node elected as head of cluster. When this count breaches threshold value then a node will not be reelected as CH in future iterations. This approach makes sure power is exhausted uniformly across different iterations. Impact of this variable is noteworthy as node's decreasing ability in performing CH operations in successive iterations is considered crucial which is denoted in Eq. (7).

$$\text{Node History} = 1 - \sum\sum_{i=1}^{N_{Hist}} \left(\lambda^{i} * \text{Hist}(n, i)\right) \tag{7}$$

$$\text{where, } Hist(n,i) = \begin{cases} 1 & \textit{node n was selected as CH in Round "r} - i\text{"} \\ 0 & \textit{otherwise} \end{cases} \tag{8}$$

In the preceding Eq. (8), *r* denotes ongoing round, whereas *r-i* shows previous rounds.

4.5 Node Centrality

Node centrality is a characteristic that determines how a node is positioned in relation to its neighbors. The mobile BS selects every participant and computes (Δ^2) using Eq. (9) from the selected node to other nodes proportional to network dimension (Ntw_Dim). In case if there are any issues in computing this value then Algorithm uses a default values when it sees any outlier in final value computed and most likely that input set is discarded. The power consumed by member nodes to transfer data to CH is decreased by dropping the value of deductions, because transmission energy is proportional to the squared distance.

$$\text{NodeCentrality} = \frac{\sqrt{\sum_{i=1}^{\text{NDensity}} \Delta_i^2 / \text{NDensity}}}{\text{Ntw\_Dim}} \tag{9}$$

where, *NDensity* is node density, and Ntw_*Dim*is network dimension.

4.6 Node Mobility

Base station movement indicates that while the sink moves to different locations, the distance between the mobile sink and CH increases or decreases depending on the mobile sink's velocity and movement.

4.7 Determination of Fuzzy Logic

A fuzzy system in Fig. 2 has three components-fuzzification, inference engine, and de-fuzzification. Fuzzification component converts the input variables to the fuzzy sets. Inference engine unit gets these transformed inputs which analyses the inputs for using it in fuzzy logic. Mamdani fuzzy concept [26] is adopted for expert system's inference engine. It is a rule-based method that generates output using the IF…THEN… rules and does not necessitate complex calculations. Defuzzification refers to the process of determining each node's chance of selecting CH. Among the existing methods available for defuzzification, Center Of Gravity (COG) method has been utilized [27] in our approach.

High (H), Low (L) and Medium (M) are variables taken in fuzzy sets for Node's Residual Energy (RE), Node Density (ND), Node History (NH) and Sink Mobility (MS). Variables used in fuzzy sets are F, C and M representing Far, Close and Medium for the node's Distance to Sink and Node Centrality. *Vl* and *vh* are the dynamic parameters for the fuzzy set for chance factor and l, rl, ml, m, mh, rh, h are middle order variables of the fuzzy set. These variables designate low, medium, high or rather low, rather medium and rather high.

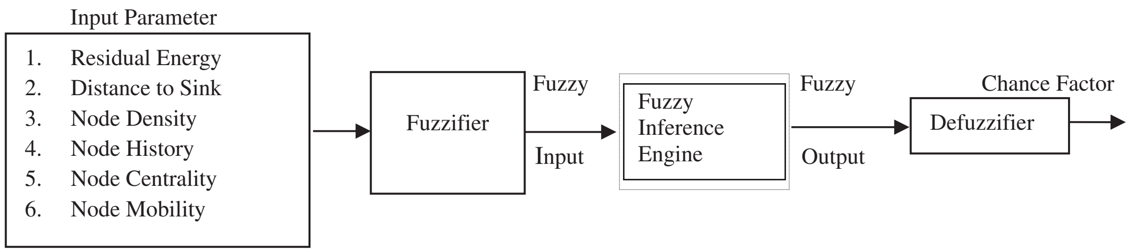

Figure 2: Operation of fuzzy logic system

In this proposed work, the trapezoidal and triangular membership functions are used to reduce calculation costs. Trapezoidal membership functions used are low, high, close, distant, nearby and far. Triangular membership functions used are Medium and Reachable. The linguistic variables very high (v-l) and very low (v-l) are constituted by functions using trapezoidal scheme whereas other variables are characterized through functions using triangular scheme. As seen in Tab. 1, the chance value possibly 3^6 = 729 can be obtained using fuzzy if-then rules as we have six fuzzy parameters and each parameter has 3 linguistic variables.

Table 1: Sample fuzzy rules

S.no	RE	Dist	ND	NC	NH	MS	CHANCE
1	Low	Close	Medium	Far	Low	Medium	Very low
2	Low	Medium	Far	Close	Medium	High	Rather Low
3	Low	Far	Close	Medium	High	Medium	Medium low
4	Low	Close	Medium	Far	Medium	Low	Medium high
5	High	Medium	Far	Close	High	Medium	Rather high
6	High	Close	Close	Medium	High	High	Very high
.	.	.	.	.	.	.	.
728	High	Far	Far	Close	Low	High	Medium high
729	High	Close	Close	Medium	Low	Medium	Rather high

Algorithm1:Proposed logic for selecting head of cluster

Input:*A non-clustered VSN, Algorithm Parameters*

Output: *List of CHs*

1. SNode: Node in the field.

2. i : Identity of the SNode.

3. SNode(i).RE: Residual Energy level of i^{th} *Node.*

4. SNode(i).Dist: Distant to Sink of the node.

5. SNode(i).ND: Node Density.

6. SNode(i).NC: Node Centrality.

7. SNode(i).NH: Node History.

(continued)

Algorithm1:Proposed logic for selecting head of cluster
8. SNode(i).MS: Mobility of Sink.
9. List.CH = 0;
10. Compute Chance of each SNode using FLS(RE,Dist,ND,NC,NH,MS)
11. Broadcast Chance to declare CH
12. In each round, choose CHs based on the highest chance value.
13. Add SNode(i) to List.CH
For each round:
14. Cluster formation depending on received intensity signal.
15. Cluster members submit data from their sensors to their CH.
16. Mobile Sink collects data from CHs.

Fig. 2 explains the selection process to elect the head of cluster and this process uses hierarchical rules, which are fuzzy in nature. Proposed FLC, as shown in figure, uses the six parameters to estimate the output variable chance for every sensor node. CH selection mechanism chooses the node with best chance which is depicted in Algorithm 1.

4.8 GA Optimized Fuzzy Rules

When developing a fuzzy model, arriving at the initial list having active rules is paramount. Designing a Fuzzy system that has the ability to manage relatively larger number of input parameters as well as fuzzy rules might be difficult owing to storage and computational complications. Furthermore count of rules is proportional to the increasing list of subsets, and accordingly the computing complexity too increases in fuzzy system. To reduce computational complication and improve interpretability while maintaining accuracy, GA-based machine learning is incorporated into the fuzzy rules refining procedure. Numerical results show that a fuzzy system optimized with a genetic algorithm outperforms traditional fuzzy logic-based methods. The inspiration at the back of this logic is noticeable, because surplus and inactive rules makes zero impact to output or efficiency of controller. As a result, redundant and inefficient rules can be eliminated from the initial set, particularly while dealing with fuzzy logic computations in real-world scenarios. List of predefined rules deployed in fuzzy algorithm (***No. of rules***), is presented in Tab. 2, which is computed using multiple parameters out of which total inputs (*m)*, total values (*k)* are critical [28]. General form of Eq. (10) is thus denoted as

$$\text{No.of rules} = k^m \tag{10}$$

Table 2: Number of rules

No of linguistic value	No of rules			
	Set1	Set2	Set3	Set4
2	2	4	8	16
4	4	16	64	256
6	6	36	216	1296
8	8	64	512	4096

Schemes that depends on genetic fuzzy logic like Genetics-Based Machine Learning(GBML) is a self-service model, this doesn't require any familiarity on related domain. For instance, GA was utilized to generate fuzzy rules in [29,30] and for fine-tuning membership functions in [31,32]. Fuzzy GBML methods mainly find its applications in fuzzy control as well as the challenges related to approximation. Key focus area of this study is arriving at limited rules with more accuracy and having ability to classify relatively larger set, so the method could function as a classifier. The proposed approach finds a compressed rule set through high fitness values assignment for fuzzy rules. The proposed rule optimization algorithm is presented in algorithm 2. Fig. 3 explains complete operational flow of our hybrid model.

Algorithm II: Rule base Optimization Algorithm

Input: *Problem Data*

Output: *Compact Rule Set*

1. Initialize generation of population RK.

2. Classify current population

a. Calculate sum of Compatibility grade

b. Find Max value of αclass h(Rj) class

3. Evaluate Fitness function

4. Rule Encoding

5. While not (termination condition) do

a. Select Ri and Rj using fitness proportionate selection

b. Apply crossover for new offspring

c. Apply mutation

6. For a subsequent run of the algorithm, use the newly generated population.

7. Update RK by deleting the worst solution

Schemes using list of fuzzy rules are frequently utilized in challenges related to classification which results in figurative analysis as per inward bound numbers phenomena. The existence of an entity named '*x'* to a random list of fuzzy scheme requires different types of information: First one is for identifying the logic or the rules, which labels corresponding category as well as degree (*e.g.*, µ*close('x')*), which we obtain *via* description of fuzzy set.

4.8.1 Fuzzy Rule Generation

Proposed system utilizes logical operators like 'if/then' rule with Fuzzy Rule generation for multi-dimensional prototype [0,1] and c-class labeling problem. Logical rules created using if/then operator are used for subsequent type in our classifier system. There are n set of inputs used for training $W_p = (W_{pl}, W_{p2},\ldots, W_{pn}), p$ = value is a range of data from 1 till 'n', belonging to diversified list of l classes ($l << n$).

Rule U_j: ***IF*** F_1 *is* M_{j1}&.....F_n *is* M_{jn} ***THEN*** G_k *is* N_{jk}

where M_{j1} till M_{jn} are the set of predefined rules operated in space [0 and 1], U_j is tag of jth set of rule, G_k is possibility grade related to Class l.

When the precursor rules are established by inherited processes, the following simple heuristic approach determines the consequent class of each logic in place [33–35].

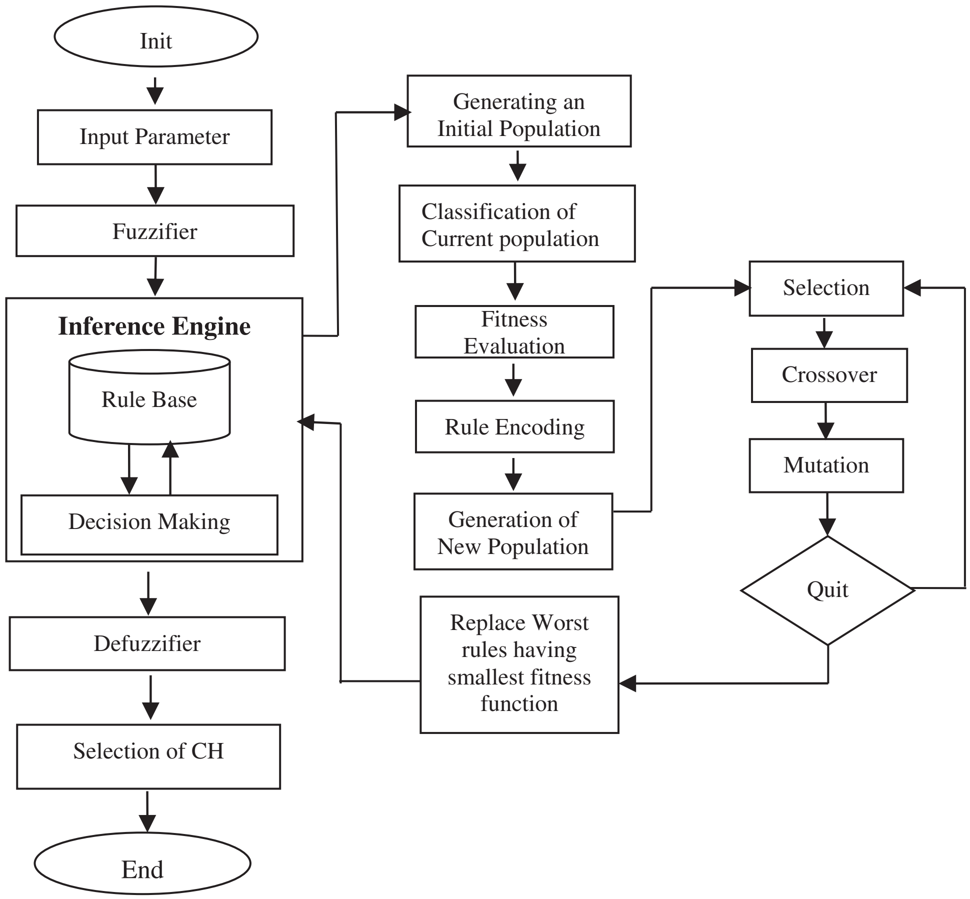

Figure 3: Operation of the proposed system

- The training patterns whose compatibility grades for each class is estimated to be

$$\alpha_{class\ h}(Gj) = \sum\nolimits_{x_p \in \text{Class}} \mu_{j1}\left(x_{p1}\right) * \ldots * \mu_{jn}\left(x_{pn}\right) \tag{11}$$

where $\boldsymbol{\alpha}_{\boldsymbol{class\ h}}$ is sum of compatibility of $\boldsymbol{xp}$'s in class $_{h}$ with rule $\boldsymbol{G_j}$ and $\mu_{j1}(.)$ is the function of predecessor rule set M$j1$.

- Identify Class $\boldsymbol{h_j}$ using Eq. (12) which has highest significance for $\boldsymbol{\alpha}_{\boldsymbol{class\ h}}\ \boldsymbol{(R_j)}$

$$\alpha_{class\ h}(Rj) = Max\{\ \alpha_{class\ 1}(Rj), \ldots\ldots\ \alpha_{class\ c}(Rj)\} \tag{12}$$

4.8.2 Encoding Rules

Succeeding label/class is readily identified using the heuristic process outlined in the preceding section; however, genetic operations of our proposed scheme affect only the rules which run previously. In our system, three linguistic values are represented by symbols (i.e., 1, 2, and 3):

High→3 *Medium*→2 *Low*→1

A string of these three symbols can be used to represent every rule. For example, following rule can be encoded like in Fig. 4.

Chromosome A	3	1	1	1	1	2

Figure 4: Sample chromosome

IF *(RE is High), (Dist is Close), (ND is Low), (NC is Low), (NH is Low) and (MS is Medium)* **Then** *(Chance is High)*

4.8.2.1 Initial Population

Count of Rules in all sets is denoted through N_{ppl}. Scheme is initialized by random set of rules derived from the previous iterations symbols and values selected drives the accuracy and efficiency of the system. Each symbol is picked at random with a 1/6 chance.

4.8.2.2 Evaluation of Each Rule

Smaller collection from the original set of rules is selected and denoted $\tilde{N}$ whose initialization parameters are modified and fresh pattern $\boldsymbol{X_p}$ is labeled based on classification algorithm. From the analysis procedures, as can be observed, list of training datasets $\boldsymbol{X_p}$ is labeled by pre-defined rule R_j.

- *Fitness Function*

To reduce list of rules by not reducing classification accuracy, the fuzzy classifier's fuzzy rule base is optimized through eliminating illogical rules and redundant rules. The fitness function consists of precisely classified rules and fuzzy rules. Optimization of fuzzy rule base is the consequence whose equation is shown in Eq. (13).

$$\mathrm{F}\left(\mathrm{R_j}\right) = \mathrm{w_c} \cdot \left(\mathrm{N_c}\right) - \mathrm{w_r} \cdot \left(\mathrm{N_r}\right) \tag{13}$$

where N_c the number of rules is correctly classified and N_r denotes fuzzy rules. w_c, w_r are associated positive weights of two components. Value returned from Eq. (13) determines if the rule is redundant. If the weight is near to zero or negative then the impact of the rule is less and becomes redundant.

4.8.2.3 Generation of New Rules by Genetic Operation

A fuzzy if–then rule duo is picked from existing population to create new rules. With the help of following selection probability based fitness proportional selection, commonly known as Roulette Wheel Selection, given as an Eq. (14), each fuzzy if–then rule in the existing set (collection of $\tilde{N}$) is chosen.

$$P_i = \frac{F(Rj) - F_{min}\left(\tilde{N}\right)}{\sum_{Rj\in\tilde{N}}\left\{F(Rj) - F_{min}\left(\tilde{N}\right)\right\}} \tag{14}$$

Proposed scheme generates two rules through consistent intersection of previous fuzzy sets Fig. 5. From the selected pair of the fuzzy if–then rules, only antecedent fuzzy sets are copulated.

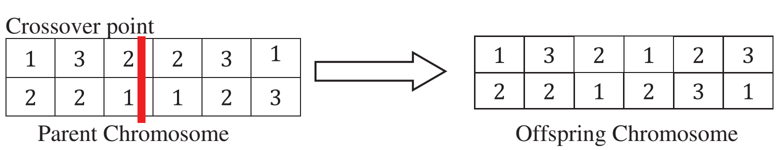

Figure 5: Operation of single point crossover for Fuzzy Set

A pre-specified mutation probability is made of use to randomly replace the generated rules with alternative set for each one of its members through crossover operation followed with mutation operation in Fig. 6. Iteratively genetic operations are used until a predetermined collection rules are formed.

Genetic-operation replaces freshly generated rules from previously specified count of rules in existing set. This study, from the existing population, rules are removed whose fitness values are lowest and refreshed using freshly formed rules. Modified rules are formed by mutation & crossover process after selection process selects a pair of rules from the existing sets. The final output generated by proposed scheme is rule set with most compact rules across all generations. Until a stopping criterion is satisfied, the genetic operation cycle is repeated. We end up with an ideal set of rules, which is decoded to generate a compact rule base after running evolutionary genetic algorithm for 1000 generations. According to Tab. 1, node with maximum residual energy has high probability of becoming CH. Furthermore, lesser distance or nearer to centrality guarantees the greater fuzzy chance.

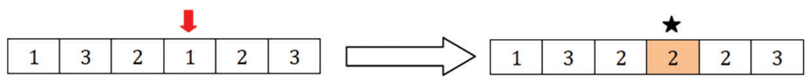

Figure 6: Mutation operation for fuzzy sets (a mutation position is denoted by *)

5 Experimental Setup

The simulation attributes and its associated values are mentioned in Tab. 3. The percentage of CH between 5 and 10 provides the most beneficial energy conservation in VWSN. Excessive energy consumption can occur for CH under two criteria's, when percentage is less than 5 because of increase in number of entities in cluster. Alternatively other criteria, where the setup has more than ten cluster heads, cluster creation events like selection, broadcasting, member request, and consent from CH itself can cause higher energy consumption between nodes. Existing clustering algorithms: LEACH-ERE [36], LEACH [37] are chosen as references for testing the proposed method. The metrics used for performance evaluation are network life span and energy utilization. Simulation software MATLAB is used to conduct experiments which find its application in multitude operations with respect to variety of applications including controllers, Internet Of Things (IoT), Deep Learning (DL), data transmission and communication, labeling, image recognition, surveillance and so on.

Table 3: Simulation parameter and values

Parameter	Value
Network size	*300 * 300* m^2
The number of nodes	*200–400*
Data packet size	*4000 bits*
Initialization Energy	*1J*
E_{elec}	*100 nJ/bit*
E_{DA}	*5 nJ/bit/signal*
E_{fs}	*15* $pJ/bit/m^2$
E_{mp}	*0.0020* $pJ/bit/m^4$

6 Performance and Comparisons

6.1 Rule Reduction

Evaluation of presented methodology which generates fuzzy rules for classification problems is done through simulation. The proposed approach based on fuzzy labeling incorporates learning procedure of fuzzy logic. Tab. 4 explains the parameters used in the algorithm.

Table 4: Genetic algorithm parameters

Parameter name	Value
Maximum no of iteration	*1000*
Collection Size	*100*
Crossover rate	*0.8*
Mutation percent	*0.02*
w_c	*1*
w_r	*0.1*

We can get undersized system depending on list of rules that is fuzzy in nature having lower accuracy when using maximum weights. This could mean that weight W_r for number of fuzzy rules in fitness function governs the trade-off between classification performance and system size as far as fuzzy rule-based systems are concerned. During learning, several rules were decommissioned automatically by optimization approaches discussed earlier.

Generated outcomes prove that proposed method has the ability to arrive at efficient rules having more accuracy and less computational time. From Tab. 5 it can be observed that obtained fuzzy rule bases are very accurate. The table also shows the rules that remained after optimization process. Optimization algorithm resulted in meaningful decrease of rules count per rule base from the initial numbers based on value obtained. The results also confirm the accuracy of rule bases did not decline when rules count were minimized.

Table 5: Results using GA based Machine Learning

Metrics	Value
No of Rules in Rule Base	*729*
Attributes	*6*
Classes	*3*
Classification Rate %	*96.7%*
Compact Rules after Optimization	*80*

6.2 Energy Consumption

Amount of energy consumed is proportional to network life any chance in one parameter affects the other. Sensor nodes absorb most of the energy when transmitting and receiving data packets, resulting in rapid energy depletion. Power is considered invaluable and limited in important monitoring contexts such as military surveillance, as most sensors are used in unattended and unattended environments, where it is often not possible to replace the battery. Only with lower energy consumption is it possible to develop real-time applications. The graph below in Fig 7 illustrates amount of energy utilized in our novel scheme in contrast to the existing models like LEACH-ERE. Our proposed model has a significantly lower average power consumption of 0.05 joules, indicating that it is a likely candidate for implementation in large, critical real-time applications where power management is critical.

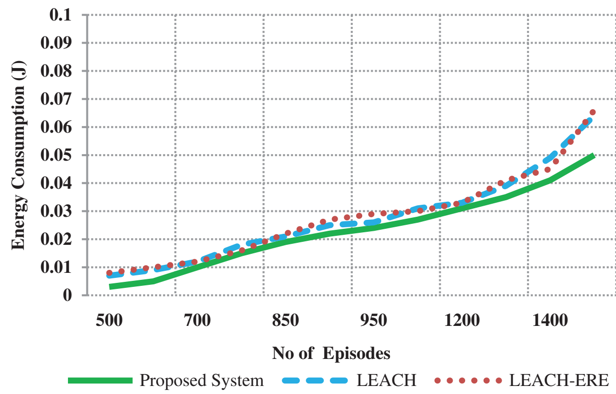

Figure 7: Energy consumption

6.3 The Network Lifetime

Longevity of the network and energy saving have always been the primary goals of any wireless network. VWSN suffers from a number of difficulties, including hotspot, energy-hole, and crowd centre effects, which drain the energy of deployed visual sensor nodes and reduce network longevity. Our model proposes addressing the aforementioned concerns by mobile sinks, rendezvous sites, selecting best path using reinforcement learning approach, and detecting abnormalities *via* detection. The graph below in Fig. 8 displays network lifetime, which is calculated based on its operating capabilities computed as time elapsed between network inception and death of earliest node (FND). The earliest node in LEACH dies after 200 episodes, while the first node in LEACH-ERE dies after 300, but in our suggested model, the first node dies only after 1000 episodes, which is substantially superior and demonstrates that the algorithm works incredibly well to improve performance.

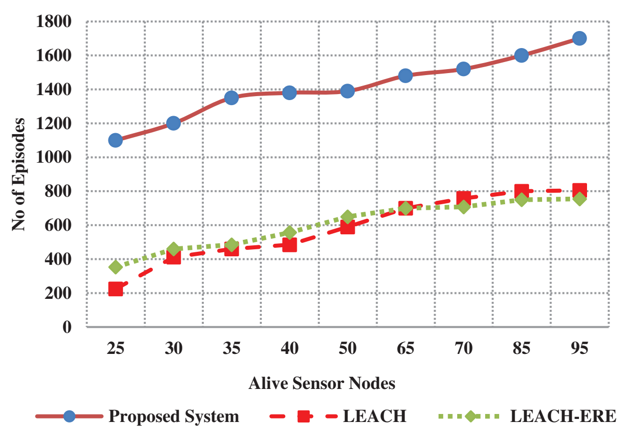

Figure 8: Network lifetime

6.4 End to End Delay

The e2e latency is calculated by adding delays for queuing, data communication, propagation, and processing. End to End Delay (EED) is a critical number that defines the overall efficiency of the system. EED measurement and assessment must be performed with exceptional precision to assure the effectiveness of a proposed plan. The geographical and temporal distribution of EED across the network has an impact on an application's long-term deployment and functioning. Reduced overhead as a result of adopting an effective routing paradigm lowers the EED and assures the required QoS-based performance. The EED comparison of our proposed system with current methods is given below in Fig. 9, where we achieved. a minimal EED of 5 ms, which is much better than the 9 and 9.5 ms produced by earlier methodologies.

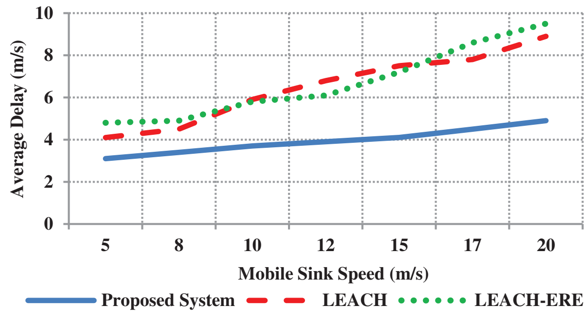

Figure 9: End to end delay

6.5 The Time Complexity

Time complexity analysis is carried out, LEACH and LEACH-ERE algorithms have lesser time complexity, as they are older, fundamental, uncomplicated and can be conveniently executed. However, their performances as far as energy consumption is considered are not effective as newer algorithms have improvised with respect to classic clustering approaches. Our novel scheme exhibits more or less same value for this parameter when compared to existing schemes, but proposed system offers best performance due to less energy consumed and increased lifetime of entities in network. Therefore, our proposed system holds higher and wider prospect of being implemented in real time WVSN applications.

7 Conclusion

Energy consumption of sensor nodes are considered crucial and it is the most constrained resource in WVSN environments, with that view in mind, we have proposed a protocol that consumes less energy while selecting cluster using Fuzzy based rules and GBML. Density of active node, distance, mobility and energy levels are few critical parameters used in selecting head of cluster. The simulation results were compared with existing protocols like LEACHERE in terms of FND, HND & LND. Our method shows promising performance in selection of CH along with optimal clusters generation. The benefit of innovative CH selection is due to fitness function (GA) derivation which enhances the overall network life span. We took into account six variables-residual energy, distance, node centrality, node density, node history and mobility. The objective has been to create a mechanism for learning fuzzy rule bases using GA along with optimization of fuzzy rule bases to eliminating irrelevant and duplicate rules. Through computational experiments it can be concluded that proposed approach can generate fuzzy models with compact rules set while maintaining rule base accuracy. The simulation results showed that our algorithm could increase classification accuracy along with minimizing fuzzy rules count. In future work the proposed scheme can be improvised by optimizing the process as the quantity of rules is still considered high. It is inferred that desired quality of results can be obtained with lesser rules through optimization process using fitness function.

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