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SPECTRUM AWARE FUZZY CLUSTERING ALGORITHM FOR COGNITIVE RADIO SENSOR NETWORKS

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ABSTRACT

This paper proposes a SAFCA for a self-organized CH selection within a CRSN. The algorithm caters CR and WSN constraints by exploiting the dynamic spectrum access and fuzzy inference technique for an energy efficient CRSN. It utilizes channel availability and fuzzy parameters of residual energy, communication cost and node distribution. The simulation measure the significant of the selected parameters. The first stage investigates the impact of inclusion of fuzzy inference towards the channel availability in the clustering algorithm, meanwhile the second stage explores the significant of the fuzzy parameters. The performance metric of network stability i.e. FND and network lifetime i.e. HNA are measured to determine the energy efficiency of the clustering algorithm. The results show the algorithm outperforms SACA, SAFEC, SAFEN and SAFCN of FND, HNA, number of alive nodes and energy consumption.

Keywords: cognitive radio; wireless sensor node; clustering; channel availability; fuzzy.

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1. INTRODUCTION

WSN technology has been operating on the industrial, scientific and medical (ISM) spectrum bands in accordance to the IEEE 802.15.4 standard. However, the bottleneck in the ISM bands has significantly degraded the WSN performance [1]. In pursuit to overcome the crowded spectrum band, the WSN research has begun to adopt the CR technology. A CR technology harvest the idle portion of licensed spectrum allocated to the licensed user known as the Primary Users (PU) for a secondary spectrum assignment. It offers an available spectrum for a medium to transmit data.

Integration of CR and WSN forms a network of CR enabled wireless sensor nodes. The CR enabled wireless sensors perform an identical to WSN function such as monitoring and surveillance with a dynamic spectrum allocation for the data transmission. The dynamic spectrum allocation, from the idle PU spectrum, differentiates CRSN from the existing WSN technology. The added CR capabilities together with the energy and computing constrained of the existing WSN demands a new protocol. The current WSN protocol operates on a static spectrum setting [2] will not suitable for CRSN which operates on dynamic spectrum. The CRSN protocol has to cater for both the spectrum aware of CR and the energy and computation constraint of WSN. Therefore, an optimal spectrum awara energy efficient algorithm is crucial in extending the CRSN network lifetime.

The CR sensor node sourced its energy from a non-rechargeable battery and consumes it during a sensing, computation and data transmission operations. As majority energy is consumed during data transmission, an efficient transmission is crucial to sustain the network lifetime. Clustering has been acknowledged for its energy efficiency as compared to direct transmission. In clustering, node relays the data to the nearest CH rather than directly to the base station (BS) or sink node. The node consumes less energy due to the shorter distance to the CH and relies on CH to finalize the data transmission to the BS. A high energy requirement on CH may lead to early node death to a low energy CH node. Meanwhile, an improper CH election may influence the rate of death and shorten the network lifetime. Therefore, intervention of early energy exhaustion and rate of death is crucial for a better CRSN network lifetime.

In CRSN, clustering operation is deployed for spectrum sensing detection [3-6] in addition to the data transmission [2, 7-9]. The existing CRSN algorithms have been designed to improve the network lifetime through energy efficient clustering mechanisms. The CRSN clustering algorithms such as CogLEACH [2], LEAUCH [3] and CogLEACH-C [4] highlight the dynamic frequency environment as part of the CH selection criteria. Both CogLEACH [2] and CogLEACH-C [4] introduce a spectrum aware clustering algorithm to improve a CRSN network lifetime. Inspired by LEACH [5], a popular low energy distributed clustering algorithm in WSN, CogLEACH addressed the dynamic channel environment by utilizing the channel availability in the CH election. CogLEACH-C [4] extended the work of CogLEACH by adding an energy parameter in CH selection for a centralized architecture. The centralized architecture of CogLEACH-C has a high network overhead and energy consumption as compared to the distributed CogLEACH in the cluster formation process. LEAUCH [3] is a CR clustering algorithm that controlled the size of cluster of a CH to overcome the hotspots problem in the multi-hop transmission. In [6], node degree and distance to BS are added to the channel availability parameter in the CH selection. One major observation in [2-3, 6] is the exclusion of energy parameter in the CH selection. This resulted to a possibility that the clustering algorithm may nominate a very low energy CH node causing an early energy hole. Therefore, energy parameter should be included in the clustering algorithm to prevent such event for occurring. The consideration of channel availability as part of a clustering parameter in [2, 6-8] is unfounded in WSN due to its static spectrum allocation. The channel availability is importance in CR because a high number of idle channel offers flexibility for channel switching and minimizes re-clustering due to changes in channel states [7]. The channel availability parameter has not only been applied in the clustering algorithm but also in solving the channel sensing order [8-9] and spectrum assignment [10].

In a dynamic channel environment, both CH and CM require a common idle channel to communicate and form a cluster. Two nodes cannot link when they do not shared a common idle channel even though they are closely located to each other. There are two types common channel constraints in CRSN i.e. pairwise and groupwise requirements. A pairwise channel constraint requires a common idle channel between a CH and a particular CM only. In contrast, a groupwise channel constraint demands an identical idle between a CH and all its CM nodes, a more strict requirement than a pairwise channel constraint. A higher number of common idle channels provides stability to the cluster as more channels available for node to link with the CH. DSAC [11] is a distributed spectrum-aware clustering, deployed the K-means clustering and groupwise channel constraint for CRSN clustering. In DSAC, all nodes exchange its intracluster distance before it can merge with adjacent nodes. Repetitive information is exchanged until the BS notifies an optimal cluster number has been achieved. Then, a node with a maximum energy is elected as CH in the cluster. The extensive exchange of information and reliance of BS lead to higher network overhead renders DSAC unfeasible for a large-scale network. Another CR clustering algorithm, BECHR [12] also employed a groupwise channel constraint and adopt an energy threshold to enhance a CRSN network lifetime. The BS receives constant energy updates from nodes and selects a new CH when a current CH energy fell below a threshold value. The BECHR nodes consume high energy from the frequent and direct update to the BS. The frequent communication generates high network overhead and high interference to the nearby PU. Although energy parameter is used in CH selection, DSAC and BECHR shares high energy requirement from the high network overhead. A weighted approach, the Cluster Head Determination Factor (CHDF) [7] proposed a channel availability and 1-hop neighbour for clustering in the cognitive ad-hoc network (CRAHN). The CHDF has a higher network overhead. Furthermore, the infinite energy model of CRAHN is not practical for CRSN. Reinforcement learning algorithm and pairwise channel constraint is introduced to cluster a CRSN [13]. The optimal policy is used to maximize spectrum holes detection and minimize energy consumption in data transmission. A candidate CH is predetermine using probability method using channel availability, residual energy and percentage of clusters as parameters. The agent used machine learning technique and learn from neighbouring CH for optimal clusterhead selection. The algorithm converges after sufficient exploration and exploitation of its state-action pairs. Subsequently, final clusters are decided by the BS. The BS communication has a high energy requirement and should be constraint only for data transmission only.

In [14], the researchers presented a fuzzy logic algorithm to CRSN clustering to minimize energy consumption and extend the network lifetime. A two fuzzy input parameters i.e. energy and distance to BS, are used in the CH selection. Fuzzy logic is one of the prominent algorithm in WSN clustering dated back as early as 2005 based on the work in [8] and still observe by other WSN researchers till now. Fuzzy logic is capable of reducing the computational overhead which is suitable for energy constrained system of WSN and CRSN. Fuzzy logic has the advantage of using imprecise data, fuzzy sets and inference rules unlike the mathematical equations [9]. As a consequence, the fuzzy algorithm is capable of handling uncertainties of real time application more accurate than the probabilistic model [10]. However, the fuzzy algorithm in [14] does not take advantage of the dynamic CR radio environment unlike the clustering algorithms in [2, 6-8] in reducing the energy consumption. Fuzzy logic algorithm is not only been employed in clustering the CRSN but also deployed in channel sensing order [8], spectrum assignment [10] and cooperative sensing [15].

In this paper, a spectrum aware fuzzy clustering algorithm (SAFCA) is proposed. The goal is to reduce the total energy consumption and maximize the CRSN lifetime. Despite the fuzzy logic algorithm has been explored in [14], the proposed algorithm will apply both spectrum aware and fuzzy logic in energy efficient clustering CRSN which is not explored by [14]. Multiple parameters are carefully selected as single parameter CH does not provide sufficient energy efficiency [11]. The proposed SAFCA has three fuzzy parameters contrary to the two parameters used in [14]. The parameters are the residual energy, communication cost and node distribution with the addition of channel availability. The issue of network overhead can be addressed by the deployment of fuzzy logic as it can offset the overhead of collecting and calculating energy and location of each node in the network [16]. Node distribution is locally determined which minimizes the BS communication unlike a node density. A node density requires regular updates of nodes' status to BS and BS updates on the node population to all nodes. Hence, it has high network overhead and high energy consumption than node distribution Furthermore, node distribution describes the distribution of neighbouring nodes. A closer neighbouring nodes can lead to a smaller intra-cluster communication cost and less energy being consumed by CM.

This paper is structured as follows: In section II, the related work associated to clustering techniques is presented. In section III, the CR network model and the fuzzy inference system (FIS) is described in detail. In section IV, the simulation results of the proposed algorithm are discussed. Lastly, a number of conclusions is presented in section V.

2. METHODOLOGY

This section describes the system model and algorithm for an energy-efficient spectrum aware fuzzy logic clustering scheme.

2.1. CRSN Network Model

The network consists of N CR sensor nodes coexist among M PU operating on a set of non-overlapping orthogonal C channels. Both CR sensor nodes and PU are randomly deployed and non-mobile. The CR sensor nodes are homogeneous where all sensor nodes has the same energy level of 0.5J and communication range. The unlicensed band are used as common control channel (CCC) to facilitate the exchange of control information between CR sensor nodes as mentioned in [21]. The CRSN is model as an undirected graph represented by G (V, E), where V and E are a set of nodes and communication links in the CRSN respectively.

The CR sensor node will use the channel unoccupied by a PU and is refrained from accessing a PU occupied channel within a distance of 20m to prevent from interfering the PU [6]. The proposed clustering mechanism is independent of any PU activity model. A two state Markov process as depicted in Fig. 1 is selected to model the channel busy and idle states. The steady state probability of a channel c in idle state is determined using the Equation (1) in [2]:

$$P_c^{idle} = \frac{q_c}{p_c + q_c} \tag{1}$$

where q_c is the transition probability of channel c will be idle in the next time slot when it is busy in the current time slot and p_c is the transition probability of channel c will be busy in the next time slot when it is idle in the current time slot. The p_c and q_c reflects the intensity of PU activity in the CRSN network. It is assumed that the transition probabilities are accurately estimated to determine the P_c^{idle}.

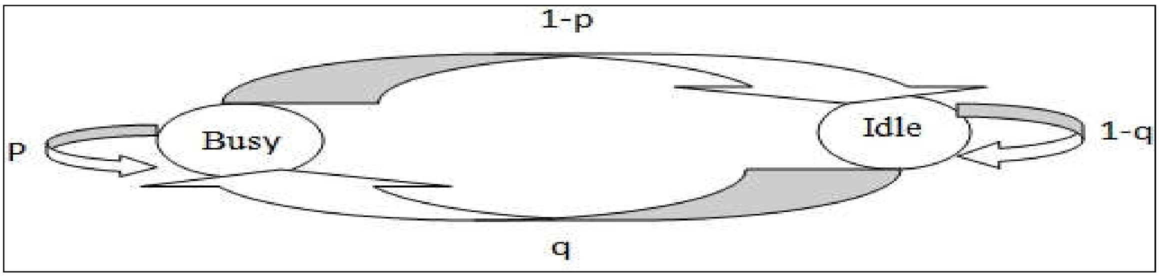

Fig.1. Two State Markov model for the channel c (1≤ c ≤C)

The limited energy of the CR sensor node is consumed for transmission, reception and aggregation activities. Based on the radio energy model in [5], the respective energy consumption are determined using Equation (2)-(4) respectively.

$$E_{TX_i} = \begin{cases} \left(E_{elec} + \varepsilon_{fs} * d^2\right) * l, & \text{if } d \le d_o \\ \left(E_{elec} + \varepsilon_{mp} * d^4\right) * l, & \text{if } d \ge d_o \end{cases}$$

(2)

$$E_{RX_i} = E_{elec} * l$$

(3)

$$E_{DA_i} = E_{elec} * l \quad (4)$$

where d is the path of energy flows from the source node to the BS. l denotes the size of data in bits and is fixed throughout the whole simulation. E_{elec} , ε_{fs} and ε_{mp} are the energy consume by the CR sensor circuitry and RF amplifier respectively. The signal path is model as a freespace or multipath propagation depending on the threshold value d_o defined by Equation (5).

$$d_o = \sqrt{\varepsilon_{fs} / \varepsilon_{mp}} = 86.7\text{m} \quad (5)$$

The energy consumed as CH node is expected to be higher from the many tasks it carried out which includes the reception, aggregation and transmission. In contrast, a CM node only consumes energy for transmission only.

2.2. Clustering Algorithm

The CR sensor nodes configure the CH distributively and form a cluster in every round to cater the spatial variations in the dynamic radio environment and prevent early energy hole. The clusters is resolved after data has reached the BS through a CH. A round is defined as the interval between two successive cluster formations. The proposed SAFCA algorithm is described in Algorithm 1. The proposed algorithm employed probabilistic model in LEACH [5] for node to self-elect itself as a candidate CH. Then, the algorithm employs channel availability and fuzzy logic on the residual energy, communication cost and node distribution parameters for node to compete with neighbouring candidate and finalize itself as a CH.

Algorithm 1. Spectrum Aware Fuzzy Clustering Algorithm (SAFCA)

```
/*each clustering round*/
Input: nodes local and locally sourced information
Output:Cluster head CHs and Clusters

Begin
Input: SA, RE, CC, ND,
For all nodes
    Generate Random Number, RN
    If(RN< P(n_i))
        node_i ←Candidate CH
    Endif
Endfor

/*calculate channel availability and chance
For all Candidate CHs
    Calculate Chance FIS{RE,CC,ND}
        node_i (SA)← {C_1,C_2,...C_n}/size(Channels)
        node_i (SAF)← node_i(SA) x node_i (F)
            Broadcast (SAF) to all neighbours
Endfor

/*compete with neighboring candidate CH
For every Candidate CH,advertise SAF parameter
    If candidate node_i (SAF) > Neighboring candidate node (SAF)
        CH_i←node_i
        Neighbor node join CH_i if (C_{n_i} ∩ C_{CH_j})
```

else

node_i join Neighbor node if $(C_{n_i} \cap C_{CH_j})$

Endif

Endfor

Broadcast Node ID of CH_i

/*form cluster

For Remaining Nodes

node join nearest CH if $(C_{n_i} \cap C_{CH_j})$

Endfor

End

In each round, node n_i determines its likelihood of becoming a candidate CH using the probability in [5]:

$$P(n_i) = \begin{cases} \dfrac{p}{1 - p*(r \bmod \frac{1}{p})}, & \text{if } n_i \in G \\ 0, & \text{else} \end{cases} \tag{6}$$

where p is the ratio of candidate CH in the network, r is the current round and G represent a node that have not been a CH for the last $\frac{1}{p}$. The probability model in Equation (6) prevents any previous round CH being re-elected in a subsequent round to avoid the early node death incident. However, the probability cannot avoid a low energy CH node from nominating itself as a candidate CH. Therefore, the SAF parameter comes in to remove a low energy candidate from being a CH.

A candidate CH node calculates a SAF parameter, a composition of channel availability and chance from a fuzzy logic. The channel availability value (SA) is determined in Equation (7) [2].

$$SA = \frac{c_i}{m} \tag{7}$$

where c_i is the number of idle channels observed by candidate CH and m is the total number of channels. A candidate CH node with higher number of idle channels has better opportunity to link with adjacent CM nodes resulting a stable cluster. Therefore, a node with a high SA is a better CH candidate. However, sole dependency on channel availability does not guarantee an optimal solution [9] in a CH election.

Chance (F) is calculated using the fuzzy rule based on three parameters, i.e. the residual energy (RE), the communication cost (CC) and node distribution (ND). Selection of fuzzy parameter are carefully nominated to minimize direct interaction with BS. A direct communication can be originated from sending updates to BS, i.e. node status or receiving updates from BS, i.e. statistic of alive nodes. These updates require high energy due to the long distance to BS and interference from the transmission. Hence, selection of parameter of the proposed SAFCA is constraint to node own information and locally sourced data as to minimize interference to PU and reduce energy consumption to network overhead. The first fuzzy parameter is node residual energy (RE), the remaining energy of a candidate CH. It is a significant parameter to a CH from the high energy requirement of CH. The second parameter is the communication cost (CC), defined as the distance between a candidate CH and BS. It is calculated using the received signal strength. Since the node is static, the CC value remained fixed throughout the node lifetime and is also derived from the node itself. CC illustrates the magnitude of energy consumed by a CH to relay the data to the final destination. A CH closer to BS is more favourable because it has low CC value compared to a faraway CH. The third fuzzy variable is the node distribution (ND) within the perimeter, R of a candidate CH. Node distribution may effect the energy consumption of a node [17]. The variable of R describes the average radius of a preferred cluster dimension defines by Equation (8) [18]

$$R=\sqrt{\frac{x*y}{\pi np}} \tag{8}$$

where x and y is dimension of network area and n is the total nodes. Node distribution describes the closeness of the nearby nodes. It is the ratio of the sum of distances of all neighbours node and the maximum distance of the neigbours node i.e. if all the neighbours located at the boundary R can be calculated.

$$\text{Node distribution}=\frac{\sum_{i=1}^{\#neighbour}\sqrt{(x_i-x_{CH})^2+(y_i-y_{CH})^2}}{\#neighbour*R} \tag{9}$$

where (x_i, y_i) is the coordinate of n_i. The node is aware of the number of alive nodes within the R through a local information exchange. Therefore, update from BS is unnecessary and reduce energy consumption from long and direct communication with BS. At the same time, it reduces the interference towards the PU as communication is limited to its neighbouring nodes. The lower the ND value, the lower the energy consumed for the intra-cluster communication by CH and CM nodes. Both CC and ND values are applicable to any network size.

Table 1 lists the three fuzzy parameter and their membership function, respectively. All fuzzy inputs has been set with identical membership function of low, medium and high. Higher membership value of 3 is assigned to the most favourable membership function while lower membership value of 1 to the least favourable membership. In term of residual energy, a high RE value is a favourable condition, hence the high membership function is assigned a value of 3. In communication cost, a medium CC value is defined as the most favourable node position to be elected as a CH. Therefore, a medium CC value is assigned the highest membership value. Since a low ND value translates to a low energy consumption of CH and CM, it is assigned the highest membership value. Consequently, the most favourable CH should be having a high membership function of residual energy, a medium membership function of communication cost and a low membership function of node distribution. The membership value will be used to determine the output membership function in Table 2.

Table 1. Input membership function

Input	Membership Function
Residual Energy (RE)	Low (1), Medium (2), High (3)
Communication Cost (CC)	Low (2), Medium (3), High (1)
Node distribution (ND)	Low (3), Medium (2), High (1)

Fig. 3-5 shows the fuzzy sets of the three fuzzy parameters i.e. residual energy, communication cost and node distribution respectively. Both low and high membership functions are characterized by a trapezoidal shape and the medium membership function using a triangular shape.

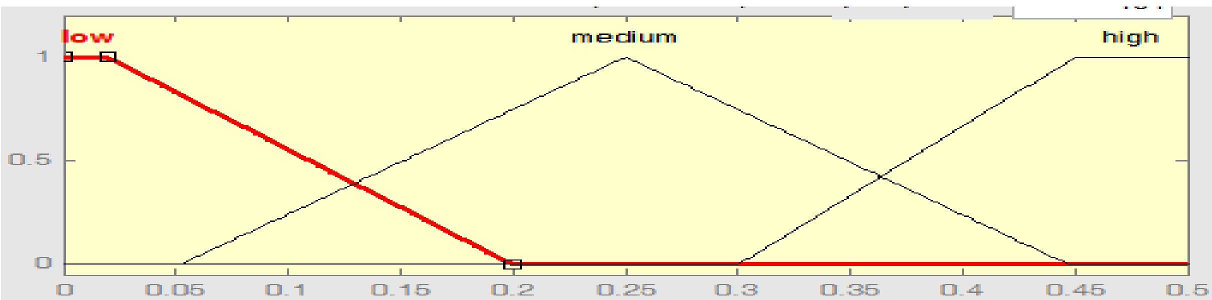

Fig.2. Degree of membership versus residual energy

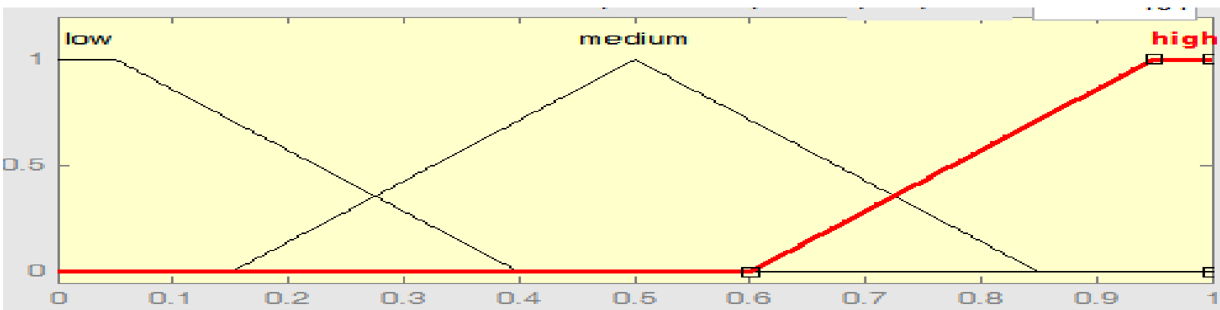

Fig.3. Degree of membership versus intercluster communication cost

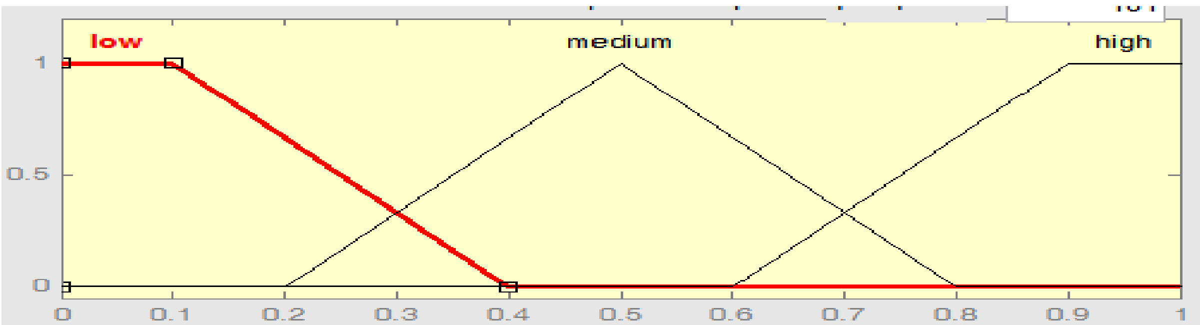

Fig.4. Degree of membership versus node distribution

The chance generated by the fuzzy output is defined according to nine membership functions, as listed in Table 2. Again, the trapezoidal shape is selected for the lowest and highest membership function i.e. very weak and very high. For the rest of the membership, the triangular shape is chosen to describe the degree of membership and the values of the individual levels. The degree of the chance membership function is shown in Fig. 5.

Table 2. Chance membership function

Output	Membership Function (MF)
Chance (F)	Very Weak (1), Weak (2), Relatively Weak (3), Low Medium (4), Medium (5), High Medium (6), Relative High (7), High (8), Very High (9)

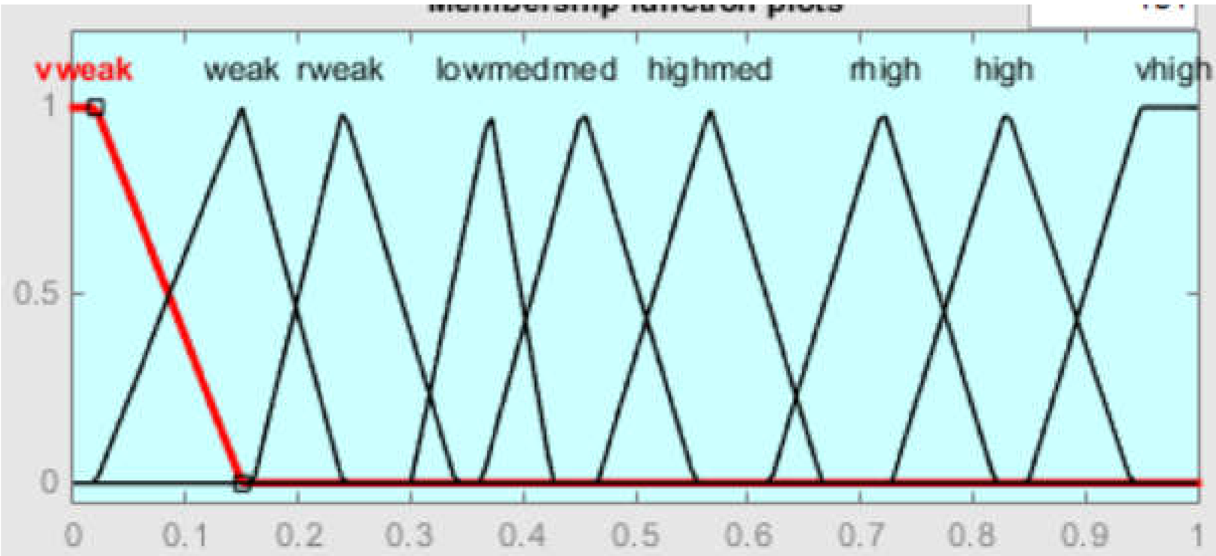

Fig.5. Degree of membership versus chance value

The twenty-seven rules are used by the fuzzy inference as listed in Table 3 is defined by Equation (9):

$$MF = 2RE + CC + ND - 3 \tag{9}$$

where it is based on a best fit consideration for a node being selected as a CH. All the fuzzy parameters is added to show that the combination of the three parameters makes up a good property for a node to elect as a CH. In Equation (9), residual energy is assigned a high multiplier to indicate that node energy has a higher priority than communication cost and node distribution to take on the CH role. Table 3 shows that the lowest chance node to be elected as CH has a low degree membership function of residual energy and high membership function of communication cost and node distribution. While, the highest chance node to be elected as CH has a high membership function of residue energy and medium membership function of communication cost and low membership function of node distribution.

Table 3. Fuzzy if-then rules

Residual Energy	Communication Cost	Node Distribution	Chance
Low	High	High	V.Weak
Low	High	Medium	Weak
Low	High	Low	R.Weak
Low	Medium	High	R.Weak
Low	Medium	Medium	L.Med
Low	Medium	Low	Med

Low	Low	High	Weak
Low	Low	Medium	R.Weak
Low	Low	Low	L.Med
Medium	High	High	R.Weak
Medium	High	Medium	L.Med
Medium	High	Low	Med
Medium	Medium	High	Med
Medium	Medium	Medium	H.Med
Medium	Medium	Low	R.High
Medium	Low	High	L.Med
Medium	Low	Medium	Med
Medium	Low	Low	H.Med
High	High	High	Med
High	High	Medium	H.Med
High	High	Low	R.High
High	Medium	High	R.High
High	Medium	Medium	High
High	Medium	Low	V.High
High	Low	High	H.Med
High	Low	Medium	R.High
High	Low	Low	High

The chance crisp value is calculated using the centroid defuzzification method and the membership function in Fig. 5. Both channel availability (SA) and chance (F) values are multiplied and advertised as a SAF parameter to its surrounding. If the advertisement received by another node CH of a higher SAF parameter, the lower SAF node will reset it status to a normal node. This process eliminates redundant CH existence within the radius, R. The normal nodes then will form cluster with the nearest CH through a pair wise constraint.

3. RESULTS AND DISCUSSION

In this section, the results of the simulations of the proposed algorithm, SAFCA are presented. The performance of SAFCA is evaluated via MATLAB. The simulation parameters considered in the evaluation are given in Table 4.

Table 4. Simulation parameters

Parameter	Value
Network Size	200m x 200m
Base Station Location	100,100
Number of CR nodes	100
Number of PU	7
Number of Channel	5
Data Packet Size	4000 bits
E_{elec}	50nJ/bit
ε_{fs}	10pJ/bit/m^2
ε_{mp}	0.0013pJ/bit/m^4
E_{DA}	5nJ/bit/signal
Initial Energy	0.5 J

The CRSN nodes are deployed randomly within the defined network area and employ single hop transmission in relaying data to the BS. A desired ratio of CH, p is set to 0.2 for all simulations as it produces the most optimal result for SAFCA. The simulations are conducted in two parts. The first stage is to compare the performance of SAFCA with a spectrum aware clustering algorithm (SACA). SACA has a similarity in term of the random probability and channel availability parameter to the proposed SAFCA. While the second stage is to evaluate the impact of the fuzzy parameter of SAFCA against SAFEC, SAFEN and SAFCN.

The performance metric considered are First Node Dies (FND), Half Nodes alive (HNA) and Last Node Dead (LND). These performance metrics are commonly found in the energy efficient studies in CRSN and WSN. FND represents the number of rounds that a network has operated until a first node dies and HNA denotes an event when half of the total nodes deployed has died. The FND or death of single node is vital in sparsely deployed WSN [19] and indicates the stability period of a WSN [20]. Meanwhile, HNA metric is widely used as a measure of network lifetime in WSN [21]. LND is represented by the number of rounds when the final node dies. Eventhough, LND is sometimes used to measure the network lifetime, the network is usually render useless after a HNA. Therefore, HNA metric will be used rather than LND to indicate the network lifetime in this simulations. Lastly, the network energy is measured to determine the energy consumption of the CRSN.

3.1. Performance SAFCA against SACA

3.1.1. Node Lifetime and Stability Period

Table 5 shows the performance of the SAFCA and SACA with respect to FND, HNA and LND. The proposed SAFCA performed 12% better than SACA in the FND metric. The proposed SAFCA outperformed SACA by 11% with respect to the HNA metric. Lastly, in the LND metric of SAFCA is 17% higher than SACA. The higher FND of SAFCA proves that the stability period of SAFCA is higher than SACA. Overall, the FND, HNA and LND studies proved that the SAFCA has longer node lifetime than SACA. This shows that the adoption of spectrum aware and fuzzy logic in the proposed SAFCA clustering algorithm has enhanced the network stability and lifetime of the CRSN as compared to spectrum aware in the SACA algorithm.

Table 5. Node lifetime

	FND	HNA	LND
SACA	813	1069	1150
SAFCA	923	1204	1331

3.1.2. Distribution of Alive Nodes

Fig. 8 shows the statistic of alive node observed in each round of the proposed SAFCA and SACA until the last node died. It is observed that the number of alive node in SACA drops much earlier than the proposed SAFCA. This indicates that the SAFCA has a better network stability than SACA. It also shows that the number of alive nodes of SAFCA remains higher than SACA at each round. The rate of decrement of alive nodes for both SAFCA and SACA is almost identical, eventhough the number of alive nodes in SACA has started to decrease much earlier. This indicates that the spectrum aware fuzzy clustering, which cater both CR and WSN [22] parameters improves the node lifetime than the CR parameter only.

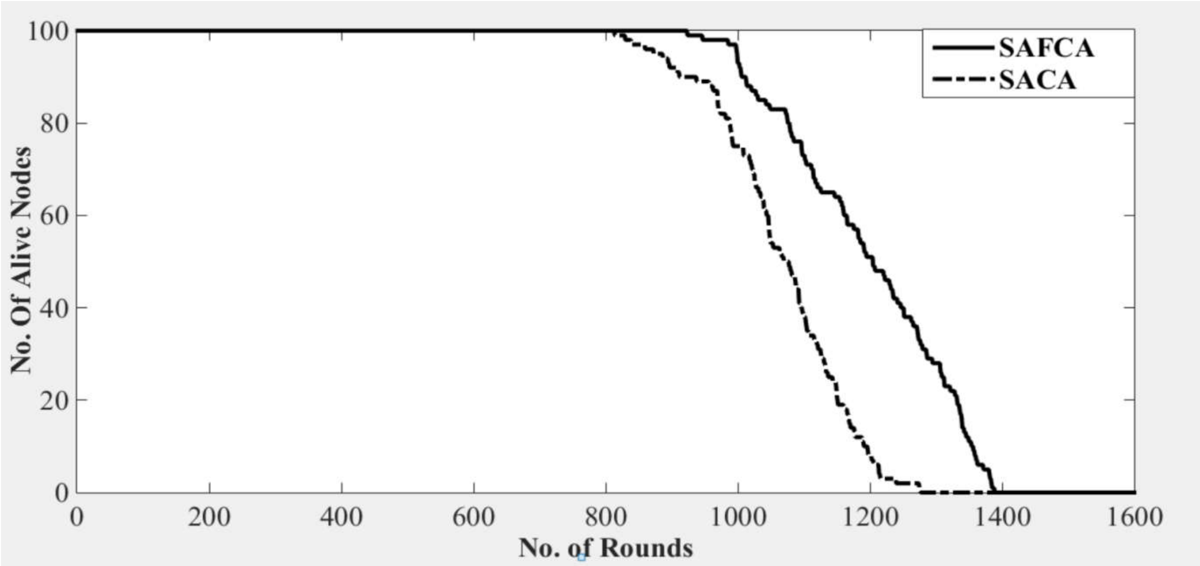

Fig.6. Number of alive nodes versus number of rounds

3.1.3. Network Energy Consumption

Fig. 7 shows the level of network energy at each round up to 1600. Fig. 7 shows that at all round, the network energy for the SAFCA clustering algorithm is constantly higher than SACA. This indicates that the energy consumption of SAFCA is lower than SACA. The rate of decrement of network energy of SACA is higher than the proposed algorithm. This resulted in the network energy of the proposed SAFCA to be consistently higher than SACA at each round. This shows that the CH elected in the SAFCA algorithm is more optimize its distance with its CM nodes and is reflected with small energy being consumed for the intracluster communication. Hence, the network energy is higher at each round.

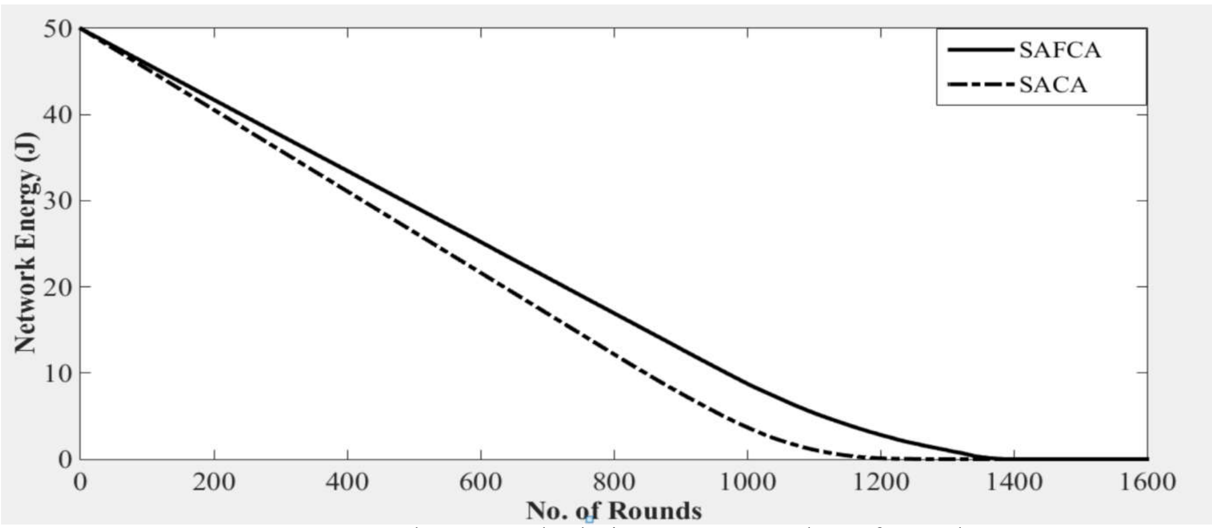

Fig.7. Network energy depletion versus number of rounds

A closer look on the network energy at each network lifetime (HNA) for both the proposed SAFCA and SACA, as listed in Table 6. The result shows that at the SACA network lifetime, the network energy of SAFCA has an efficiency of 73 % and at SAFCA network lifetime, the network energy recorded an efficiency of 96%. This proves that SAFCA improved the network energy consumption compared to SACA. The high network energy efficiency recorded by SAFCA shows it capability of selecting the optimal CH which translates to low energy being consumed in data transmission at each round. This leads to higher node lifetime and produces a longer network stability and lifetime to CRSN.

Table 6. Network energy at each network lifetime

	Energy (J) HNA of SACA	**Energy (J) HNA of SAFCA**
SACA	1.73	0.086
SAFCA	6. 35	2.73

Overall, the first study shows that the deployment of spectrum aware and fuzzy inference technique in SAFCA increases the CRSN node lifetime with respect to FND, HNA and LND compared to spectrum aware only i.e. SACA. The extended node lifetime is attributed to the optimal self-elected CH that reduce the energy consumption for data transmission. The higher FND of SAFCA proves that the network stability of SAFCA is higher than SACA. The SAFCA algorithm enables the optimal node in term of channel availability, residual energy, communication cost and node distribution to be self-elected as a CH.

3.2. Performance of SAFCA against SAFEC, SAFEN, SAFCN

The second stage of the evaluation is to investigate the influence of the fuzzy parameters in the spectrum aware fuzzy clustering algorithm. The SAFCA is evaluated against fuzzy algorithms harvested from the same parameters of SAFCA. Table 7 lists the fuzzy algorithms with its corresponding parameters and the proposed SAFCA. This study is performed to observe the significant of the fuzzy parameter i.e. residual energy, communication cost and node distribution to the network stability and lifetime of the CRSN.

Table 7. Fuzzy input parameters

	Channel Availability	Residual Energy (RE)	Communication Cost (CC)	Node Distribution (ND)
SAFCA	x	x	x	x
SAFEC	x	x	x	
SAFEN	x	x		x
SAFCN	x		x	x

3.2.1. Node Lifetime and Stability Period

Table 8 shows the simulation results of FND, HNA and LND using the respective input combination defined in Table VII. The results show that the FND of the proposed SAFCA outperforms the SAFEC by 3%, SAFEN by 2% and SAFCN by 10%. Compared to SAFCN, the FND result indicates that the combination of energy and the communication cost or node distribution has prevent an early node death by lengthening the stability period i.e. FND of the CRSN. Based on the FND of SAFCA, it is observed that consolidating the three parameters i.e. energy, communication cost and node distribution resulted in an even higher network stability than the same two parameters combined.

The results of HNA show that the SAFCA performance is better than SAFEC by 11%, SAFEN by 10% and SAFCN by 13%. The HNA results show that the proposed SAFCA has the highest network lifetime than the rest of the fuzzy algorithms with an average of 11%. In term of LND, the result of SAFCA is higher than SAFEC by 6%, and SAFEN by 9% but lower by 4% with respect to SAFCN. The combination of communication cost and node distribution parameters in SAFCN produces a highest LND which extend the network lifetime of the CRSN but at a lower network stability from a lower FND and HNA.

The FND and HNA of SAFCA results illustrate that the higher efficiency of SAFCA is attributed to the third fuzzy input parameter. Hence, the combination of the three parameters i.e. residual energy, communication cost and node distribution has extended both the network stability and network lifetime of CRSN.

Table 8. Node lifetime

	FND	HNA	LND
SAFCA	923	1204	1388
SAFEC	895	1068	1309
SAFEN	905	1085	1257
SAFCN	837	1052	1444

3.2.2. Distribution of Alive Nodes

The number of alive nodes in each round for SAFCA, SAFEC, SAFEN and SAFCN is shown in Fig. 8. It depicts that the number of alive nodes of SAFCA is higher at each round compared to SAFEC, SAFEN and SAFCN. The number of alive nodes of SAFCN decreases earlier than the rest of the algorithm. The number of alive node of SAFCA only starts to decrease after all compared algorithms has decreased. As seen in Fig. 8, SAFCA has the lowest rate of decrement of alive nodes. Meanwhile, SAFEC and SAFEN have almost the same decrement of alive nodes. SAFCN has the same decrement of alive nodes as SAFCA but the decrement of alive nodes has started at earlier round than SAFCA. Hence, the combination of energy with communication cost (SAFEC) or node distribution (SAFEN) as fuzzy parameter is insufficient to elect the optimal CH. In addition, omitting the energy parameter in the fuzzy parameter caused an energy imbalance in the network leading to early node death.

3.2.3. Network Energy Consumption

The energy consumption for all the fuzzy algorithms is recorded in Fig. 9. It depicts the network energy level in each round. The network energy continuously to decrease at a different rate. SAFCA has the lowest decrement of network energy followed by SAFCN. This indicates that without the energy parameter (SAFCN) is not able to optimize the node lifetime compared to the SAFCA, SAFEC and SAFEN which utilize the energy parameter.

The overlap of the two lines in Fig. 9 representing the SAFEC and SAFEN shows that they shares almost the same decrement in network energy. They also have the highest decrement among all the algorithms. The lower network energy decrement of SAFCA translates to a higher network energy remains in SAFCA as compared to the SAFEC, SAFEN and SAFCN at all rounds.

The network energy is then evaluated at round 1105, which is the average of HNA of the spectrum aware fuzzy algorithms as shown in Table 9. It is observed that network energy has been consumed approximately 90% for SAFCA and more than 98% for SAFEC, SAFEN and SAFCN algorithms. The additional parameter in SAFCA has further improve the energy consumption of the network by selecting an optimal CH resulted in less energy consumed in the data transmission at each round

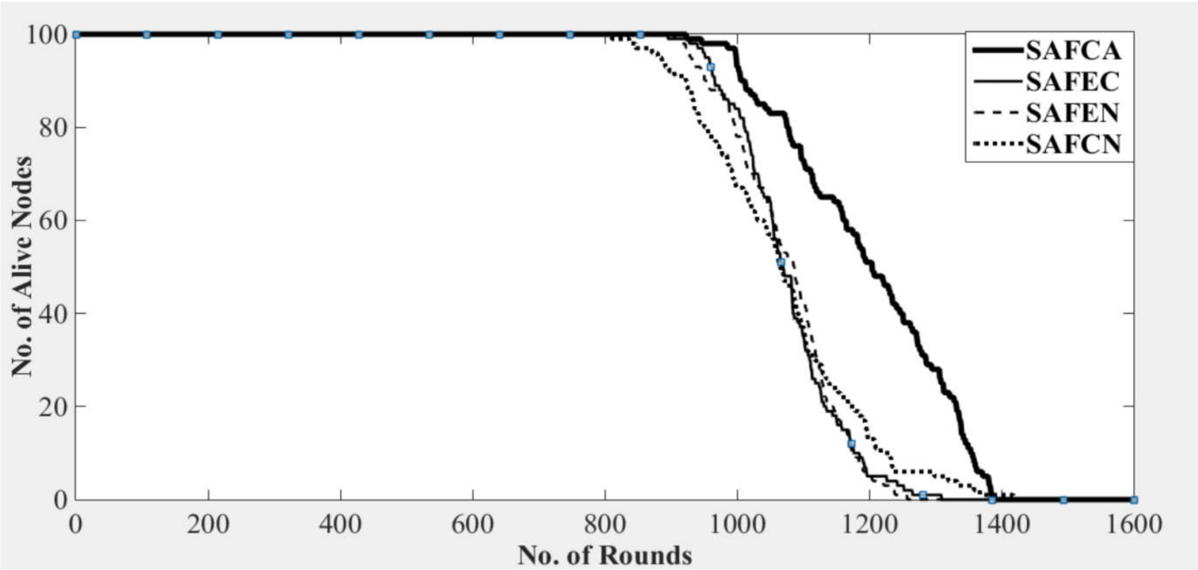

Fig.8. Number of alive nodes versus number of rounds

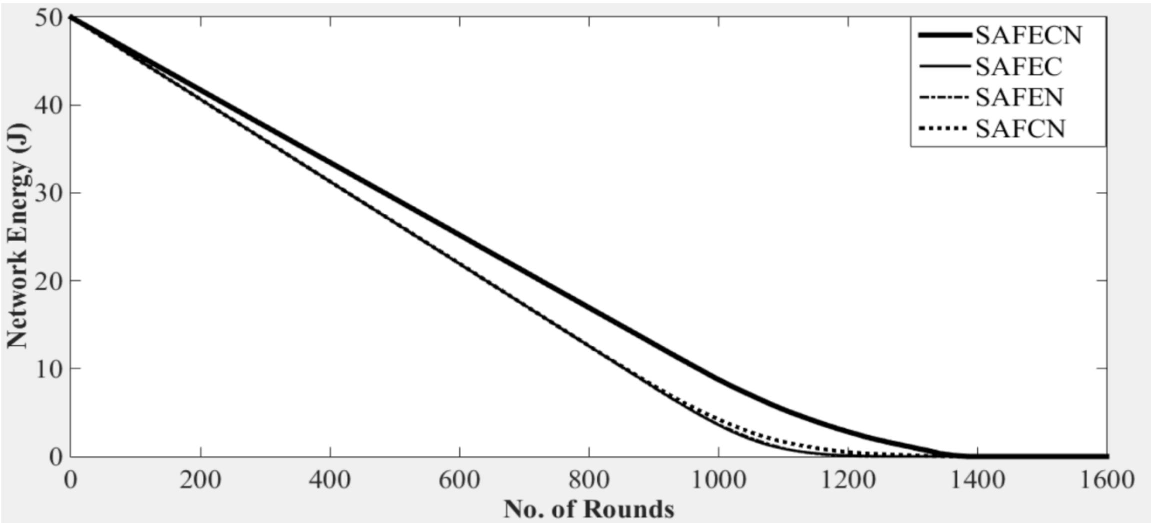

Fig.9. Network energy depletion versus number of rounds

Table 9. Network energy at round 1105

	Energy (J) at Round 1105
SAFCA	5.22
SAFEC	0.82
SAFEN	0.86
SAFCN	1.59

Overall, the evaluation on the fuzzy parameter for the spectrum aware fuzzy algorithm has highlighted three findings. Firstly, the combination of fuzzy parameters between a residual energy and communication cost or a residual energy and node distribution increase the network stability of the CRSN at the cost of the CRSN network lifetime. Secondly, the combination of fuzzy parameters communication cost and node distribution which relates to the energy consumption of the CH extend the network life time period at the expense of a shorter stability period. Lastly, using three fuzzy parameters system leads to a more energy-efficient CH than a two fuzzy parameters system.

4. CONCLUSION

A spectrum aware fuzzy clustering algorithm i.e. SAFCA is proposed and developed for energy efficient CRSN. Based on the simulation results, SAFCA has a considerably higher FND, higher HNA, higher number of alive nodes and higher network energy compared with SACA. This implies that the combination of CR and fuzzy parameters select an optimal CH than using CR only. It also points out that optimal CH selection requires handling both the CR and WSN [23] constraints. The investigation on the spectrum aware fuzzy parameters have highlighted that the energy parameter improves the FND or the network stability of the CRSN. Meanwhile, the communication and node distribution parameters extends the network lifetime through better an energy consumption in the CR nodes. Finally, a combination of the three parameters i.e. residual energy, communication cost and node dispersion SAFCA outperforms the spectrum aware fuzzy clustering algorithm of two parameters. The proposed SAFCA will further extended to address other CH issues in CR and WSN [24].

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