Malaysian Journal of Computing, 5(1): 433-445, 2020

eISSN: 2600-8238 online

SPECTRUM AWARE CLUSTERING ALGORITHM BASED ON FUZZY LOGIC FOR SENSOR BASED MONITORING APPLICATION

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ABSTRACT

In this paper, a clustering solution for periodic data gathering over WSNs using cognitive radio technology is proposed. The cluster heads (CHs) are selected according to the channel availability, residual energy, communication cost and node distribution parameters. Fuzzy logic and weight based techniques combines the four parameters for the CH selection. The cluster formation is based on the relative channel availability between the cluster member (CM) and CH to ensure stable cluster connectivity from link failure. To evaluate the proposed clustering algorithm, the performance of sensor networks is compared with CogLEACH, LEACH and CHEF routing protocols. The simulation results show that the proposed clustering algorithm effectively has a significant improvement with respect to the network stability without reducing the network instability and network lifetime. In addition, the proposed clustering solution also has a low and almost consistent CH energy consumption during the stability period indicating an efficient cluster formation.

Keywords: *Cluster Formation, Cluster Head, Instability, Lifetime, Stability*

Received for review: 12-11-2019; Published: 30-04-2020

1. Introduction

A wireless sensor network (WSN) plays an important role for remote and continuous monitoring applications in the environmental monitoring, agricultural and natural disaster prevention (Wua *et al.,* 2016) especially when the application is inaccessible because of its location and situation. These periodically applications consume the most energy than a query based and event based applications (Mohemed *et al*., 2016). Cognitive radio has become a solution to the WSN operating in the unlicensed band. The integration of the two technologies, the Cognitive Radio Sensor Network (CRSN) offers the WSN to opportunistically dynamic access in the licensed bands (Peng *et al.,* 2010). A new WSN protocol design that address the combination of both technologies is essential due to its unique characteristic and common attributes to the traditional WSN (Noor & Din, 2017).

The CRSN dynamic access in the licensed bands requires common channel for control (CCC) and data message exchange which is not an issue in the traditional WSN. Among the opted CCC approaches are the global CCC (Eletreby *et al.,* 2014); Pei *et al.,* 2015), local CCC

(Chen., 2017), dedicated CCC (Noor *et al.*, 2018) and without CCC (Chen *et al.*, 2017; Kumar & Singh, 2018). The control message size is negligible (Mehra *et al.*, 2018). However, the centralized clustering such as BECHR (Mansoor & Shahid, 2014) and DSAC (Zhang *et al.*, 2012) engaged in extensive message exchange to collect the information such as energy and location. The sensor information is commonly utilized either directly (Siqing *et al.*, 2018) or indirectly (Lee *et al.*, 2012) for optimal CH selection for energy efficiency cluster-based routing. The intra-cluster and inter-cluster connectivity in dynamic spectrum access are challenged compared to the WSN static allocation.

The CRSN is projected to address the low delay, high throughput and reliability requirements in the next generation WSN such as the Internet of Things (IoT) (Bradai *et al.*, 2015; Rawat *et al.*, 2016). Improvement of performance such as network lifetime, network connectivity, throughput, end-to-end delay and spectrum efficiency is anticipated from the strong propagation characteristic of the licensed band and the opportunistic dynamic allocation (Yau *et al.*, 2009; Ahmad *et al.*, 2015) compared to the traditional WSN.

One of the important observation in the spectrum constraint CRSN does not change the fact that energy is mostly consumed during data transmission (Chen *et al.*, 2017). Therefore, the cluster-based routing is preferable for the CRSN implementation over a flat routing for its lifetime (Tyagi *et al.*, 2015; Venkateswarlu *et al.*, 2016) and traffic efficiency (Saifullah *et al.*, 2008). The cluster-based routing also allows bandwidth reuse which promotes better channel resource allocation (Heinzelman *et al.*, 2002) is an advantage for a spectrum constraint CRSN. The optimal cluster-based routing remains an open issue in CRSN (Rawat *et al.*, 2016) with respect to the CCC, energy and spectrum constraints in addition to its low computing architecture.

High computation complexity usually involved in cluster-based routing using the optimization approach. The meta heuristic approaches such as genetic algorithm, ant colony optimization and particle swarm optimization are not suitable for WSN scalability (Jana, 2016). Low computation technique such as probabilistic and weight-based cluster-based routing is more common to cater the WSN computing constraints. The probability election for cluster head (CH) whose role to gather data from the surrounding CRSN and transmits to a Base Station (BS), does not guarantee the most suitable CH node being selected. The fuzzy logic technique delivers its output without a complex mathematical model (Rauniyar & Shin, 2015). It rules based decision reduces the processing overhead (Noor & Din, 2017). The fuzzy logic can overcome the various uncertainties in clustering process (Bagci & Yazici, 2013) unlike the weight based which rely on the exact value. The probability technique cannot guarantee that a CH will be elected. The weight based cannot prevent the same node for CH from being frequently elected which eventually affect the network stability similar to the probability technique.

The cluster-based routing consists of the cluster set up phase which covers the CH and cluster representation. Energy efficiency and balanced are two important factors in sustaining the network lifetime. To the best of our knowledge, the tentative or final CH play the role of balancing the network energy through the competitive or cluster radius. In this paper, a non-CH or cluster member (CM) is responsible to balance the network energy through the CH selection is proposed. The approach is to take advantage of the channel availability information to address the spectrum aware, common channel constraint. The main feature of the algorithm is the low message overhead and computation clustering algorithm through CH energy and CH-non CH spectrum distribution. A dedicated transceiver for CCC is also proposed to minimize switching latency for out of band communication.

The rest of the paper is organized as follows. The related works are presented in Section 2. The system model and the proposed fuzzy weight based scheme for cluster-based routing are described in Section 3. The performance evaluations are described in Section 4 followed by the conclusion in Section 5.

2. Related Works

The CRSN energy is highly consumed in communication and least consumed in computation and processing (Mehra *et al.,* 2018; Raghunathan *et al.,* 2002). The energy in signalling is negligible due to the small message size compared to the transmitted data (Bradai *et al.*, 2015). Therefore, the energy consumption is more focused on the communication task i.e. the energy for running the radio component should be optimised to prolong the CRSN network lifetime. Distributed clustering algorithm promotes local CH representation without the BS intervention. This scheme is more suitable for CRSN as the secondary user in the licensed bands which automatically solves the interference in the control and data traffic.

Low Energy Adaptive Clustering Hierarchy (LEACH) (Heinzelman *et al.*, 2002) promotes a probability model for low computation CH but best suitable CH is not guaranteed. Many algorithms such as the Energy Aware Unequal Clustering Fuzzy scheme (EAUCF) (Bagci & Yazici, 2013) and the Cluster Head Election mechanism using Fuzzy Logic (CHEF) (Kim *et al.*, 2008) uses the probability as a distributed mechanism for its tentative CH. The tentative CH undergoes a final CH selection using the output from the fuzzy logic. The fuzzy logic reduces the network overhead in CH selection (Kim *et al.*, 2008). However, the current WSN cluster-based routing algorithms such as EAUCF and CHEF do not address the dynamic spectrum access in the licenced bands (Kumar & Singh, 2018).

CRSN has attracted much research attentions in the cluster-based routing. The CRSN routing is bounded by the computation and energy constraint of the WSN in addition to its spectrum constraint as SU. The CRSN cluster-based routing shares a common parameter i.e available channel and the opportunistic access improved its network performance. A simple comparison among the common energy efficient homogeneous routing protocol for CRSN is given in Table 1. The Low Energy Unequal Adaptive Uneven Clustering Hierarchy (LEUCH) (Pei *et al.*, 2015) proposed a shorter competitive radius of tentative CH near the BS to balance the network energy. Meanwhile the Cognitive Low Energy Adaptive Hierarchy (CogLEACH) (Eletreby *et al.*, 2014), used CH rotation in each round to balance energy consumption over the network. All the algorithms implement the spectrum aware constraint to CH node for election and cluster formation where LEUACH and LEACH use the channel availability as CH election probability in CRSN. In (Zhang *et al.,* 2011), DSAC algorithm clusters the CRSN through messages exchange among neighbouring nodes and coordination of BS. The EBSAC algorithm (Chen *et al.,* 2017) proposed energy, available channel and common channel as CH election. However, CH is selected by the BS causing higher interference, is less favourable for coexistence in PU network as control communication is extended between the BS. The CH energy is used as the cluster radius to balance its network energy. The extensive message exchange in DSAC and EBSAC are not suitable in large scale CRSN. Another weight based CRSN, WCL (Kumar & Singh, 2018), selects its CH using the available channel, speed of node and interference level attributes for mobile CRSN. The cluster is established through channel rendezvous. However, the scheme does not guarantee that the selected CH can sustain the high CH energy requirement and the channel rendezvous together with the multiple transceivers demands high energy.

In (Shah & Akan, 2013), the spectrum aware cluster-based routing (SCR) algorithm based its CH selection on the spectrum energy rank. The cluster is implemented through a dedicated control channel which was not further elaborated about the implementation. However, the single interface CRSN suffer from switching latency between the dedicated control channel and the opportunistically data channel which non negligible in out of band channels. In (Fadel *et al.,* 2017), a hybrid Energy-efficient Spectral Honey bee Mating Optimization-based Clustering (ESHC) for the cluster-based routing in smart grid application is proposed. The Euclidean distance is selected as its fitness function to minimize transmission energy. The meta heuristic algorithm is not suitable for CRSN due to its high computation and complexity. The clustering algorithms (Chen *et al.*, 2017) and (Kumar & Singh, 2018) utilized exact values for CH selection and combined with selected scaling factors. However, exact parameter sensor values are often difficult to determine (Baykasoğlu & Gölcük, 2015).

Most of the CRSN cluster formation schemes are not far apart from WSN using the minimum distance. Other parameters that may affect the communication are overlook. It is worth noted that CH with higher number of channels has lower probability of link failure (Kumar & Singh, 2018). This parameter is used to define the CH selection but has not been extended to the cluster formation.

Table 1. List of Existing Energy Efficient Clustering CRSN Protocols

Protocol	COGLEACH (Eletreby *et al.*, 2014)	LEAUCH (Pei *et al.*, 2015)	SCR (Shah & Akan, 2013)	EBSAC (Chen *at al.*, 2017)	WCL (Kumar & Singh, 2018)	Proposed Algorithm
Application	Time driven	Time driven	Not specified	Time driven	Time driven	Time driven
CH selection	Probability: available channel	Probability: available channel	Weight: available channel, energy	Weight: energy, available channel, distance to BS	Weight: available channel, node speed, interference level	Weight & Fuzzy: available channel, energy, neighbour distribution, distance to BS
Cluster formation	Smallest transmission distance	Competitive radius: Distance to BS	Smallest transmission distance	Smallest transmission distance	Smallest transmission distance	Smallest transmission distance and Available channel
CCC	Global CCC	Global CCC	Dedicated CCC	No global CCC	No CCC	Dedicated CCC (Unlicensed)
Network level	Single hop	Multiple hop	Single hop	Multiple hop	Multiple hop	Single hop
Transceiver	Single	Single	Single	Single	Multiple	Multiple

CogLEACH and LEAUCH which implemented a global CCC to exchange clustering messages is difficult to meet especially for large scale CRSN (Chen et al., 2017). The SCR dedicated control channel cannot be guarantee due to PU activity (Heddure & Pingat, 2016). The EBSAC does not detail the implementation of replacing the global CCC while in WCL operates on channel rendezvous to substitute the CCC. In the proposed cluster-based routing, a dedicated CCC is proposed. Multiple transceivers are also proposed for dedicated control and data channels for energy efficiency. The control transceiver is specified using the IEEE 802.15.4 transceiver in the unlicensed band. The interface reduces energy consumption up to 94% compared to the IEEE 802.11 (Araujo *et al.,* 2012).

3. Methodology

3.1 CRSN System Model

The network consists of M Primary Users (PU), N CRSN and a Base Station (BS). The CRSN nodes are homogeneous, randomly distributed and non-mobile over the network. The nodes and BS are equipped multiple interfaces to minimize switching latency and at the same time improve the performance at the cluster and BS. There are C non-overlapping orthogonal channels licensed to Primary Users. A two state Markov process is used to model the channel busy and idle states of PUs. The unlicensed band is used as a common control channel (CCC) to facilitate the exchange of control information to construct clusters between CRSN nodes. The dedicated of the CCC will be operated on a small, low power digital interface based on the IEEE 802.15.4 standard. Therefore, the dedicated CCC and separate data interfaces prevent channel switching and conserve energy at the CCC due to low energy protocol being used.

3.2 CRSN Energy Consumption Model

The energy consumption is focused on the communication component where its energy is mostly consumed. The radio component is composed of Transmitter Electronic, Transmitter Amplifier and Receiver Electronic as shown in Figure 1. The CRSN node consumes energy to run the Transmit Electronic and Transmit Amplifier circuits during packet transmission and the Receive Electronic circuit during packet reception. Both Eq. 1 and 2 are the transmission $E_{tx}$and reception E_{rx} energy where E_{elect}=50nJ/bit represents energy consumed by the electronic circuit, ε_{fs} represents the energy factor in free space model, ε_{mp} represents the energy factor in multipath fading model and *l* represents the size of information.

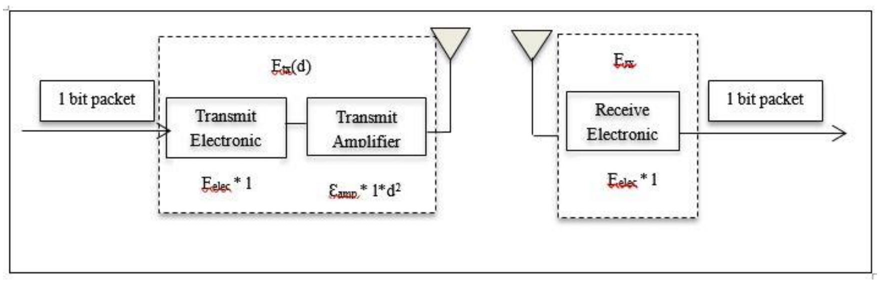


Figure 1. Radio Energy Dissipation Model

$$E_{TX_i} = \begin{matrix} \left(E_{elec} + \varepsilon_{fs} \times d^2\right) \times l & for\ d \leq d_{threshold} \\ \left(E_{elec} + \varepsilon_{mp} \times d^4\right) \times l & for\ d \leq d_{threshold} \end{matrix} \tag{1}$$

$$E_{RX} = E_{elec} \times l \tag{2}$$

where the distance threshold = 86.7m.

3.3 Spectrum Aware Clustering Algorithm Based on Fuzzy Logic (SACAF)

Figure 2 shows the fuzzy logic model consists of a fuzzifier, fuzzy decision and defuzzier blocks. The fuzzier block translates the input into the appropriate fuzzy linguistic variable which the rule in the fuzzy decision block maps to the output linguistic variables. The defuzzifier block generate the output using a defuzzification method described in (Noor *et al.*, 2018). The output is the weight value for CH selection.

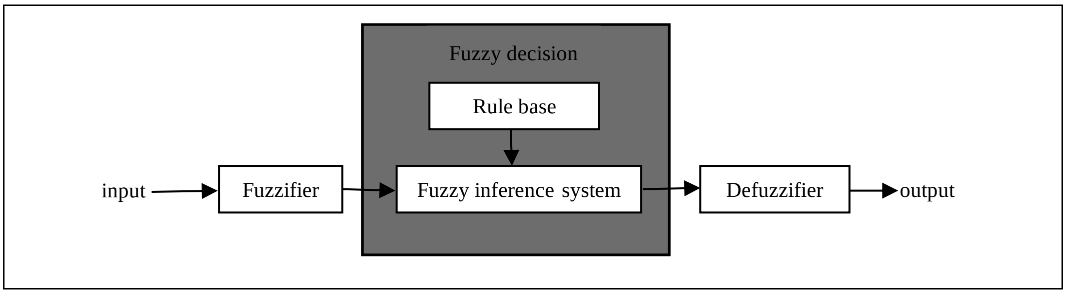


Figure 2. Fuzzy Logic Model

Leach probability model is used to determine the threshold for tentative CH. The SACAF fuzzy rule in Table 3 maps the tentative CH inputs: residue energy (RE), communication cost (CC) and node distribution (ND) to output i.e. CHChance. The CHChance combines with the channel availability to form CHprob which is used to finalize the node status as CH. The CH broadcasts a CH advertisement message consists of its ID and channel availability. If a node receives multiple CH messages, it uses the channel available information to decide the CH for cluster formation. At the beginning of the clustering phase, each sensor generates a random number and becomes eligible TentativeCH if it exceeds a set threshold value. Once a TentativeCH, it calculates its CHprob to compete as CH within its neighbours. To calculate the CHprob, the first parameter, channel availability (Ca) is used as scaling factor while the remaining three parameters residue energy(Re), communication cost (Cc) and neighbour distribution (Nd) are combined through fuzzy logic as shown in Figure 3. The communication cost relates to the normalized node distance to BS with respect to network size and neighbour distribution relates the normalised distance between the node and its surrounding neighbours.

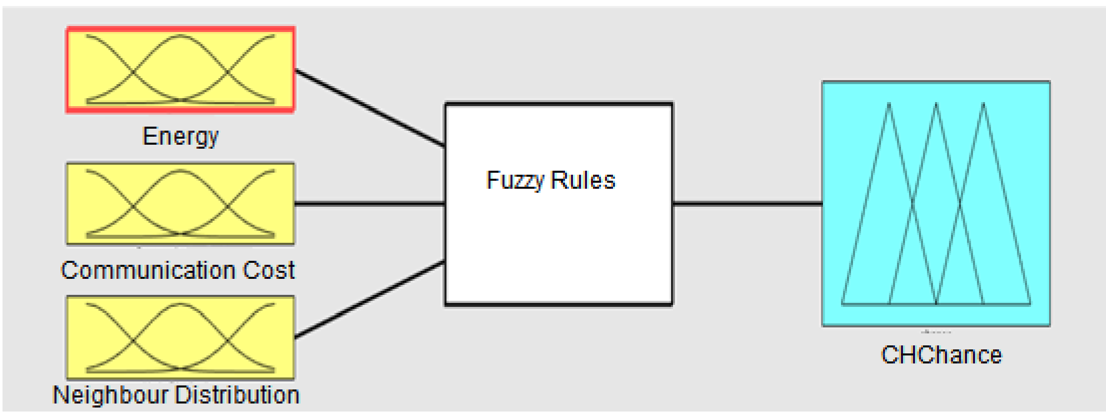
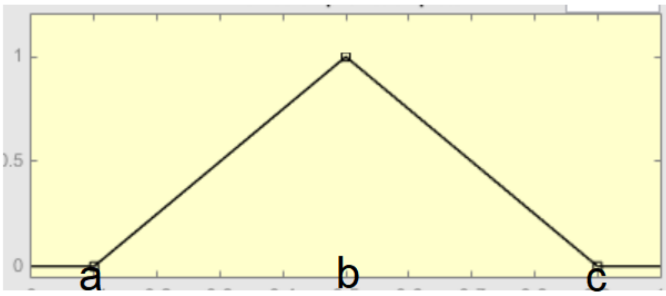


Figure 3. Fuzzy Logic Model for CHChance

The three parameters will be the fuzzy variables and assigned identical three linguistic variables (LOW, MEDIUM, HIGH) for each of the fuzzy variables. All the linguistic variables is described using the triangular membership function based on Eq. 3.



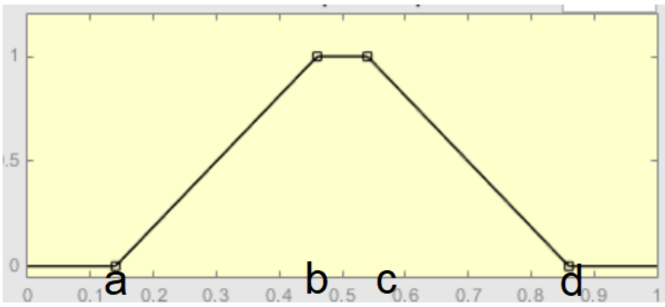
$$\begin{Bmatrix} 0, & x \le a \\ \dfrac{x-a}{b-a}, & a \le x \le b \\ \dfrac{c-x}{c-b}, & b \le x \le c \\ 0, & c \le x \end{Bmatrix} \quad (3)$$

The fuzzy output variable CHChance is determined using the fuzzy logic rule shown in Table 2. The fuzzy output is assigned with nine linguistic variables (Very Low, Low, Relatively Low, Weak Medium, Medium, Relatively Medium, Relatively High, High, Very High). Both Very Low and Very High linguistic variables characteristics are defined using the rectangular membership function based on Eq. 4.

Table 2 Fuzzy Rules for CHChance

Rules	**Input Variables**			**Output Variable**
	Re	Cc	Nd	CHChance
1	Low	Low	Low	Relatively Weak
2	Low	Low	Medium	Weak
3	Low	Low	High	Very Weak
4	Low	Medium	Low	Low Medium
5	Low	Medium	Medium	Relatively Weak
6	Low	Medium	High	Low
7	Low	High	Low	Medium
8	Low	High	Medium	Low Medium
9	Low	High	High	Relatively Weak
10	Medium	Low	Low	Medium
11	Medium	Low	Medium	Low Medium
12	Medium	Low	High	Relatively Weak
13	Medium	Medium	Low	High Medium
14	Medium	Medium	Medium	Medium
15	Medium	Medium	High	Low Medium
16	Medium	High	Low	Relatively High
17	Medium	High	Medium	High Medium
18	Medium	High	High	Medium
19	High	Low	Low	Relatively High
20	High	Low	Medium	High Medium
21	High	Low	High	Medium
22	High	Medium	Low	High
23	High	Medium	Medium	Relatively High
24	High	Medium	High	High Medium
25	High	High	Low	Very High
26	High	High	Medium	High
27	High	High	High	Relatively High

The remaining linguistic variables are described with the triangular membership function similar to the fuzzy input variables.



$$\begin{Bmatrix} 0, & x \le a \\ \dfrac{x-a}{b-a}, & a \le x \le b \\ 1 & b \le x \le c \\ \dfrac{d-x}{d-c}, & c \le x \le d \\ 0, & d \le x \end{Bmatrix} \tag{4}$$

All the values of the membership function for both the fuzzy input and output variables is defined in Table 3. The CHchance fuzzy output is then defuzzified using the Centre of Area method for its crisp value. The crisp value is combined with the Ca and broadcasts its CHChance message. The node will be CH if the CHChance is higher than the existing TentativeCH in its neighbour list.

Next, the CH nodes broadcast their id and Ca to their neighbours. The non CH nodes update its CH List and find the relative common channel Rca between the node and potential CH. Then it sends join CMJoinMsgREQ based on the higher relative channel available to reduce possibility of link failure due to the change in channel availability. CH updates its cluster list and response with corresponding common channel for data transmission. All the above communications operates on the unlicensed band.

Table 3. Membership Function Values for Fuzzy Variables

Input	Membership Function	a	b	c	d
Re	Low	-0.05	0	0.2	-
	Med	0.05	0.25	0.36	-
	High	0.25	0.5	0.6	-
Cc	Low	-0.02	0	0.4	-
	Med	0.2	0.5	0.8	-
	High	0.5	1	1.2	-
Nd	Low	-0.01	0	0.35	-
	Med	0.2	0.4	0.7	-
	High	0.5	1	1.2	-
CHChance	Very Low	-0.36	-0.4	0.075	0.15
	Low	0.08	0.2	0.4	-
	Relatively Low	0.1	0.3	0.5	-
	Weak Medium	0.2	0.4	0.6	-
	Medium	0.3	0.5	0.7	-
	Relatively Medium	0.4	0.6	0.8	-
	Relatively High	0.5	0.7	0.9	-
	High	0.7	0.85	0.9	-
	Very High	0.8	0.9	1.1	1.2

4. Result and Analysis

The performance of the proposed fuzzy algorithm is simulated using MATLAB. The CRSN network operation progresses in rounds which consists of a cluster set-up and data transmission phase. Since energy conservation is the CRSN primary objective, performance metrics such as network lifetime, energy consumed per round, and the residual energy level of sensor nodes are studied. The proposed system model uses the assumptions listed below:

1- All the CRSN nodes are homogeneous with respect to energy, hardware, communication, and computation capabilities.
2- The nodes are stationary and deployed randomly and uniformly distributed.
3- The base station position is located in the middle of the CRSN.

The metrics used to evaluate the SACAF scheme are defined as follows:

(i) stability period: number of rounds until the first node dies (FND) out,
(ii) instability period: number of rounds from the FND to the 50% node dies (HNA) out
(iii) network lifetime: number of rounds until the 80% node dies out,
(iv) average number of CH energy consumption during stability period.

Table 4 lists the remaining simulation parameter used.

Table 4. CRSN Simulation Parameter

Number of Nodes	100
Network Size	100 m x 100m
Initial Energy	0.5J
Packet size	4000 bit
Location of BS	(50,50)

Figure 4 shows the simulation results of the proposed algorithm SACAF compared to LEACH, CogLEACH and CHEF accordingly. It shows that SACAF outperforms the rest of the algorithms with respect to the network stability recording a highest FND of 1026. Both the CRSN algorithm i.e. SACAF (fuzzy) and Cogleach (probability) have a better network stability compared to the WSN clustering algorithms i.e. LEACH (probability) and CHEF (fuzzy) can be attributed to its spectrum aware property in this case the channel availability parameter. The network instability period of SACAF and the CogLEACH is lower than the LEACH and CHEF algorithms. The network lifetime result indicated that the node with LEACH and CHEF algorithm suffers from packet drops as the PU reoccupy the channel which the nodes currently utilizing. Meanwhile, the higher network lifetime of the spectrum aware algorithms i.e. SACAF and CogLEACH is attributed to the transmission avoidance of any packet on a busy channel which eventually cause a collision. The spectrum aware transmission saves the node's energy which further extend the overall network lifetime. The SACAF has a higher network stability with a slightly lower network lifetime and network instability to CogLEACH. The comparable network lifetime and network instability is due to the higher number of alive nodes during the network stability period of SACAF participating in the data transmission as shown in Figure 5. At the beginning of network instability period of SACAF, the node population of CogLEACH has reduced to approximately 94%. This translates to higher energy consumption in a longer period (between 684 to 1026 rounds) compared to CogLEACH which explained the lower network lifetime of SACAF than CogLEACH. Therefore, SACAF outperforms the CogLEACH, CHEF and LEACH algorithm in the CRSN operation.

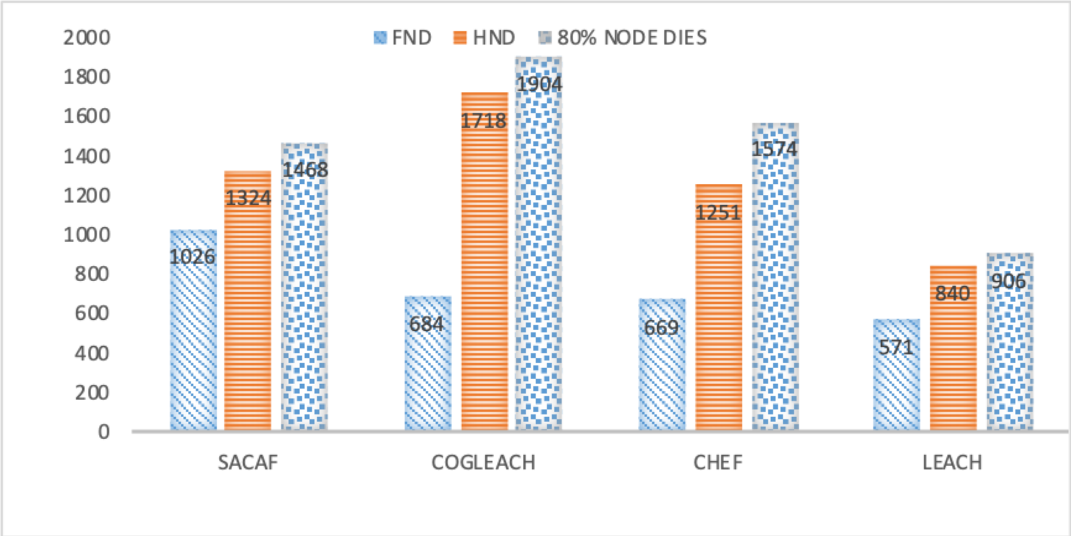


Figure 4. Performance of network stability, network instability and network lifetime

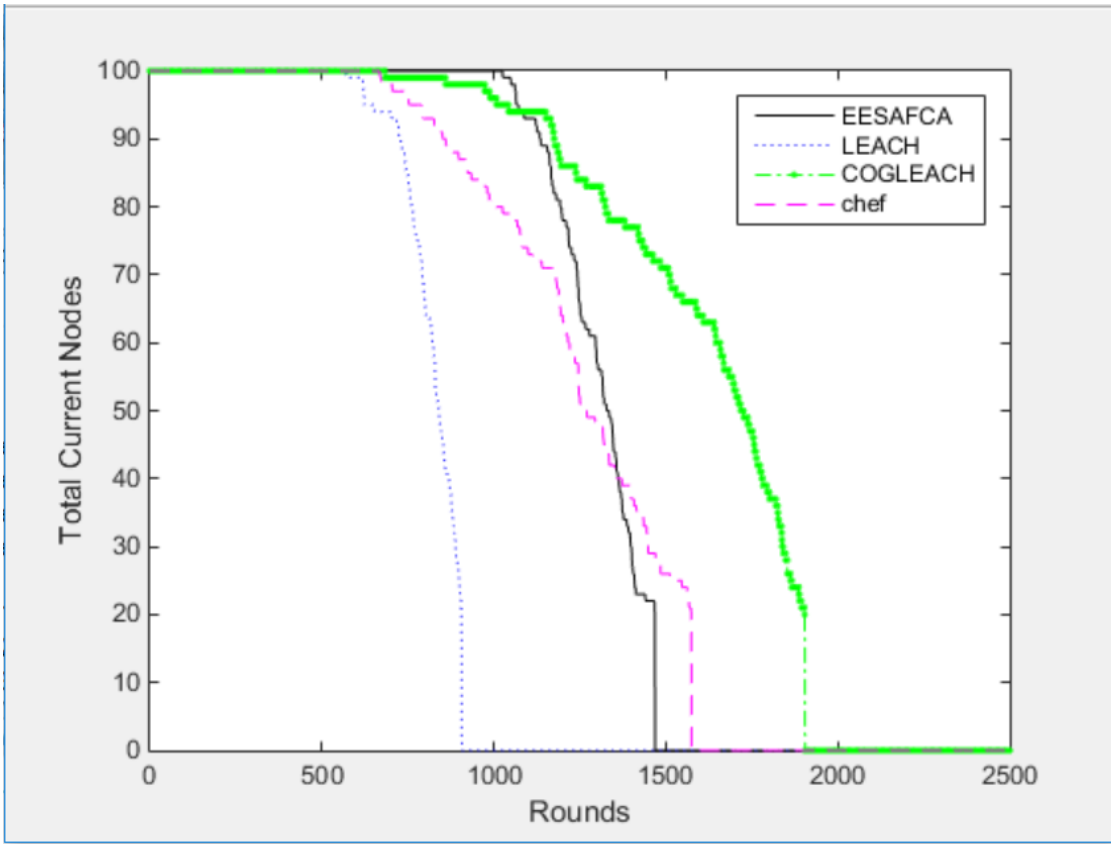


Figure 5. Statistics of Alive Nodes for respective clustering algorithms

The CH energy consumption is important in the performance study as CHs carry more tasks than the CMs. Figure 6 shows the comparison of CH energy consumption as observed from round=50 to round=65. Between these rounds, the SACAF has the lowest and more consistent CH energy consumption as opposed to the other three clustering algorithm. The next clustering algorithm which has a lower CH energy consumption is CogLEACH followed by CHEF and LEACH. The higher fluctuation of CH energy is recorded by both CogLEACH and LEACH as they are probability based techniques. Eventhough the CogLEACH probability is based on the spectrum aware parameter but the single parameter is insufficient to select the optimal CH in each round which imply the fluctuation in CH energy consumption. Both the SACAF and CHEF CH energy consumption are less fluctuating than the probability based CH selection. These can be attributed to the multiple parameters used in the CH selection delivering an optimal CH node for the data transmission. In addition, the consideration of CH energy in cluster formations help in balancing the overall network energy. The spectrum aware parameter in SACAF enables lower CH energy consumption as data transmission is the target on idle channel. This approach minimizes collision with the PU activity and eventually saves energy from retransmission. The SACAF suffers less collision and less packet drop due to competing PU channels than the CHEF and LEACH clustering algorithm for its channel availability in CH selection.

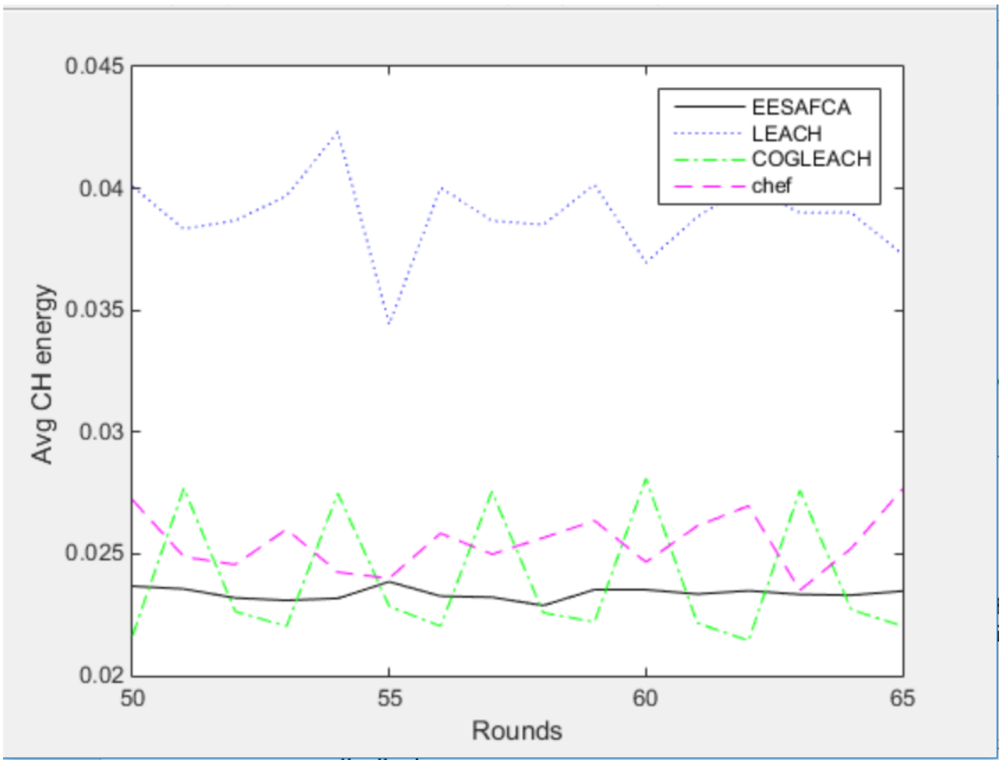


Figure 6. Statistics of Average CH energy consumption for respective clustering algorithms

5. Conclusion

It is observed that the spectrum aware clustering algorithm outperform the existing non-spectrum aware clustering algorithm with respect to network stability, network instability and network lifetime. The spectrum aware element in the clustering algorithm helps ensure the CH nodes have the most channel availability in their channel lists. The CH nodes with most available channels have a lower possibility of link failure and less packet drop due to collision with PU nodes. The proposed clustering algorithm shows that the spectrum aware parameter is insufficient to select the optimal CH selection and cluster formation due to the lower performance of CogLEACH.

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