International Journal of Electronics
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/tetn20

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Version of record first published: 30 May 2012.

To cite this article: Ashutosh Kumar Singh , N. Purohit & S. Varma (2013): Fuzzy logic based clustering in wireless sensor networks: a survey, International Journal of Electronics, 100:1, 126-141

To link to this article: http://dx.doi.org/10.1080/00207217.2012.687191

International Journal of Electronics, 2013
Vol. 100, No. 1, 126–141, http://dx.doi.org/10.1080/00207217.2012.687191

Fuzzy logic based clustering in wireless sensor networks: a survey

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(*Received 17 November 2011; final version received 29 March 2012*)

Wireless sensor networks (WSNs) have limited resources, thus extending the lifetime has always been an issue of great interest. Recent developments in WSNs have led to various new fuzzy systems, specifically designed for WSNs where energy awareness is an essential consideration. In several applications, the clustered WSN are known to perform better than flat WSN, if the energy consumption in clustering operation itself could be minimised. Routing in clustered WSN is very efficient, especially when the challenge of finding the optimum number of intermediate cluster heads can be resolved. Fortunately, several fuzzy logic based solutions have been proposed for these jobs. Both single- and two-level fuzzy logic approaches are being used for cluster head election in which several distinguished features of WSN have been considered in making a decision. This article surveys the recent fuzzy applications for cluster head selection in WSNs and presents a comparative study for the various approaches pursued.

Keywords: wireless sensor network; cluster head selection; fuzzy logic; lifetime; membership function

1. Introduction

Wireless sensor network (WSN) has found its application in many areas in the last few decades. Military applications, smart homes, habitat monitoring, wildlife protection, fire detection, industrial automation, etc. are a few of them. The role of WSNin today's world is becoming increasingly important. This has been made possible due to technical advancements in past few decades which have resulted in the production of comparatively cheaper, smaller and computationally efficient sensor nodes. Smaller size of nodes has made possible highly dense deployment of nodes resulting in more accurate and precise data. In most cases, the sensor nodes have to rely on the limited amount of energy. Replacing these energy sources is practically not possible. The researchers have suggested several schemes for maximising the energy-efficiency in doing the basic operations of sensing and data transmission. Clustering techniques is most promising among them. When sensor nodes are randomly deployed, then they are required to form clusters and select one node as cluster head which is responsible for collecting data from its cluster and forward it towards the sink. The cluster head election is an important problem which directly affects the lifetime of WSNs. Figure 1 shows data transmission in a clustered WSN.

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Figure 1. Data transmission in clustered WSN.

The probabilistic clustering protocols such as LEACH, HEED, etc. perform clustering and save significant amount of energy in data transmission (Heinzelman, Chandrakasan, and Balakrishnan 2004; Younis and Fahmy 2004). Periodically other nodes become cluster head and form their own clusters. In LEACH protocol, decision is taken by nodes whether or not to become cluster head in the current round. Each node selects a number between 0 and 1. If the number is less than a threshold, then that particular node becomes a cluster head for that particular round. This technique of random selection of cluster heads offers many advantages such as easy implementation, scalability, etc. But it does not guarantee about sufficient energy and optimal distribution. LEACH follows single-hop transmission where as HEED supports multi-hop transmission in forwarding the data from cluster head to base station. Another algorithm PEGASIS is also useful for prolonging the lifetime of WSNs (Lindsey and Raghavendra 2001). In this scheme, a node communicates only with a close neighbour. This reduces the amount of energy per round. Researchers have shown that this scheme gives better performance than that of LEACH. This scheme distributes the energy load evenly among the sensor nodes in the network. Distributing the energy load among the nodes increases the lifetime and the quality of network. This scheme shows further improvement as the size of the network increases. TEEN and APTEEN are other protocols used for prolonging the network lifetime and efficiency (Manjeshwar and Agarwal 2001a, b).

Non-uniform distribution of cluster heads, high overhead, etc. reasons accounts for poor performance of probabilistic clustering techniques. A number of definitions of lifetime of WSNs have been proposed by many researchers, e.g. the time until the first node dies, the time until the WSN is disconnected in two or more than two parts, the time until the half of the node has died, etc. Several variants of above probabilistic schemes use these definitions of lifetime for indicating their superiority in one terms or other.

Recently, several fuzzy based clustering algorithms have been proposed which have the advantage of better distribution of cluster heads after each round of clustering. It ensures much lower overall energy consumption in data transmission thus prolonged lifetime. Exploration of such approaches is the primary motive of this study. It is organised as follows. In Section 2, the fundamentals of the fuzzy logic system are discussed. In Section 3, different fuzzy logic algorithms for cluster head selection along with rule base table are presented. Section 4 presents a comparison among all the fuzzy based algorithms along with a table of comparison. Section 5 contains concluding remarks.

2. Fuzzy logic approach

Computational intelligence is a branch of engineering which has got its inspiration from nature. It has several tools like fuzzy logic based systems, ant colony scheme, artificial neural network, swarm intelligence, etc. The utility of suitable computational intelligence tools in various problems of WSNs has been elaborated in Iram, Sheikh, Jabbar, and Minhas (2011) and Raghavendra, Kulkarni, Förster, and Venayagamoorthy (2011). Fuzzy logic approach has been widely recommended for WSN due to its low

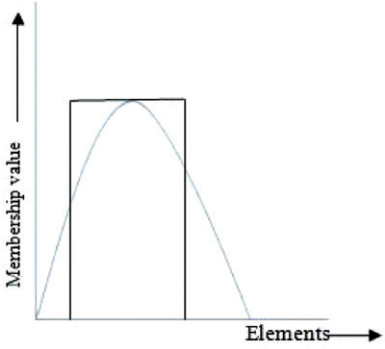

Figure 2. Fuzzy set and membership function.

computational complexity. It has already shown its potential in many fields, e.g. control system engineering, electrical engineering, etc. In control system engineering fuzzy logic based controllers give better performance than that of conventional controllers. In a number of cases, fuzzy logic controllers give improved performance in terms of overshoot minimisation. Fuzzy system is a useful tool that can make decision even there is insufficient data. Fuzzy logic systems (FLSs) do not need exact mathematical model of the system. Therefore, fuzzy logic is a useful tool for designing controllers for nonlinear and complex systems. The fuzzy sets are the sets which do not have sharp boundaries like crisp sets. In a fuzzy set an element belongs to the set to a certain amount ranging from 0 to 1, which is called as membership function. Figure 2 shows fuzzy sets and membership functions.

In a classical theory, membership of an element of set is in binary term means either element belong to the set or does not belong to the set, fuzzy is the extension of classical theory. In fuzzy theory element have varying degree of membership. Fuzzy logic uses the whole interval between 0 and 1 to describe human reasoning. For any set A, a membership function on A is any function from A to the real unit interval [0, 1]. The membership function which represents a fuzzy set A is denoted by $\mu_{A.}$ $\mu_A(x)$ is value of element x in set A is called membership degree of x. The membership degree $\mu_A(x)$ quantifies the grade of membership of the element x to the fuzzy set A. If the value of x is 0, it means x is not a member of set A and if value of x is 1 then x is fully member of fuzzy set. Common membership function used in fuzzy set are Gaussian membership function, Triangular membership function, Trapezoidal function, etc.

Type-1 FLSs are constructed from type-1 fuzzy sets, which were introduced in 1965. They have been successfully applied to many fields, but researches have shown that type-1 FLSs may have difficulties in modelling and minimising the effect of uncertainties. To overcome the limitations of a type-1 FLS, the concept of type-1 fuzzy sets was extended into type-2 fuzzy sets by Zadeh in 1975. A type-2 fuzzy set incorporate uncertainty about the membership function into fuzzy set theory. Symbolically distinguish between a type-1 fuzzy set and a type-2 fuzzy set, a tilde symbol is put over the symbol for the fuzzy set. The membership function of a general type-2 fuzzy set, $\tilde{A}$, is three dimensional, where the third dimension is the value of the membership function at each point on its two-dimensional domain that is called its footprint of uncertainty.

Fuzzy logic is an important tool for decision making, even if there is insufficient information. Figure 3 shows the block diagram of fuzzy logic mechanism.

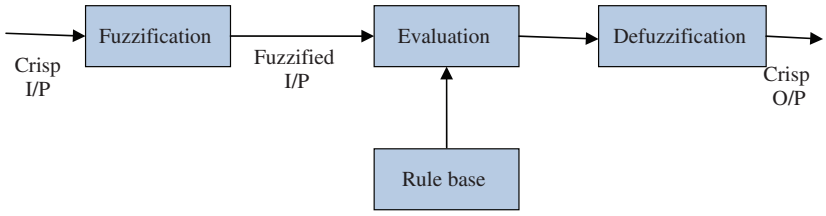

Figure 3. Fuzzy logic block diagram.

First of all, input data are fuzzified into a number of fuzzy sets. In FLSs, rule base is prepared on the basis of past experience. Defuzzifier converts fuzzy output in to a crisp output. Type-2 fuzzy set has also been used to analyse the lifetime of WSNs. There are many sources of uncertainties in type-1 fuzzy sets. Sometimes meaning of the words that are used in the type-1 fuzzy sets can be uncertain. Linguistic variables are used in fuzzy sets and these words mean different things to different people. Type-1 fuzzy set is not able to address these types of uncertainties. In case of type-2 fuzzy sets their membership functions are also fuzzy. Therefore, type-2 fuzzy sets have potential to address such uncertainties. For type-1 fuzzy set membership function is two dimensional, while for type-2 fuzzy set membership function is three dimensional. This third dimension is used to model the uncertainties of type-2 fuzzy systems (Mendel and John 2002).

Fuzzy logic is widely used in sensor networks and has shown improvement over other approaches. A number of issues of WSN, e.g. security, data fusion, and clustering have been addressed using fuzzy logic. Fuzzy systems have been successfully used for data fusion in sensor networks. Some researchers have used fuzzy logic for congestion estimation in sensor networks. Fuzzy logic has also been used for event detection through WSNs. The application of fuzzy logic in clustering the sensor nodes is surveyed in this study.

3. Fuzzy logic based algorithms for clustering

A typical snapshot of cluster heads and the respective clusters in the WSN using a leading probabilistic approach is shown in Figure 4.

It can be easily observed that the energy consumption in intra-cluster as well as inter cluster communication is very high. If the clusters are appropriately formed by choosing the *proper node* as the cluster head then the energy saving can be enhanced to several folds. Residual energy, concentration, centrality, etc. parameters are required to be simultaneously considered in defining the *proper node*. The fuzzy logic principles are the natural choice in such a scenario. Hereunder various fuzzy logic based clustering techniques are described.

3.1. *Energy-efficient cluster head selection*

Hu, Shen, and Kang (2009) have proposed energy-efficient cluster head selection (NECHS) mechanism based on fuzzy logic. They consider two factors; number of neighbour nodes and node residual energy, and generate a single variable, the probability

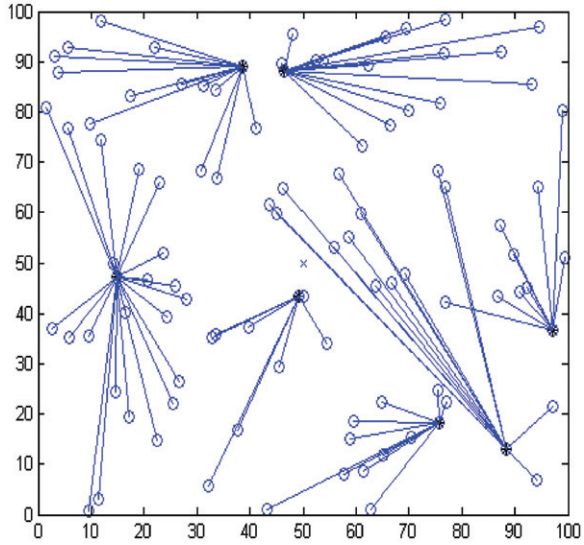

Figure 4. Clustering in WSN using probabilistic approach.

of cluster head selection. Centre of gravity method has been used for defuzzification. The simulation results show significant improvement over LEACH protocol.

Fuzzy rules for NECHS algorithm:

Set of node number	Set of remaining energy	Probability of cluster head selection
Few	Very low	Very low
Few	Low	Very low
Few	Medium	Low
Few	High	Medium
Medium	Very low	Very low
Medium	Low	Low
Medium	Medium	Medium
Medium	High	High
Many	Very low	Low
Many	Low	Medium
Many	Medium	High
Many	High	Very high

3.2. *Cluster head election mechanism using fuzzy logic*

It has been illustrated that the overheads involved in collection and calculation can be reduced by adopting CHEF technique. Thus, the network lifetime can be extended. In CHEF, two parameters are considered for cluster head election: energy and distance (Kim, Park, Han, and Chung 2008). Simulation results of this model shows better lifetime than that of LEACH.

Fuzzy rules for CHEF algorithm:

Energy	Local distance	Chance
Low	Far	Very low
Low	Medium	Low
Low	Close	Rather low
Medium	Far	Medium low
Medium	Medium	Medium
Medium	Close	Medium high
High	Far	Rather high
High	Medium	High
High	Close	Very high

3.3. *Cluster head election using two-level fuzzy logic*

In article (Torghabeh, Totonchi, and Yaghmaee 2010), two-level fuzzy logic is used for the selection of cluster head. In the first level, the nodes are selected on the basis of energy and number of their neighbours. Then in the second level, the overall cooperation of nodes is considered with three parameters: centrality, proximity to base station and distance between cluster heads. In this study most qualified sensor nodes are selected using two-level FLSs. In terms of network lifetime, this scheme gives better performance than that of LEACH and CHEF. The fair load distribution and lesser variance of energy consumption demonstrate the efficiency of this algorithm.

Fuzzy rules for local level:

Energy	Number of neighbours	Qualification in local level
Low	Low	Very small
Low	Medium	Small
Low	High	Rather small
Medium	Low	Medium small
Medium	Medium	Medium
Medium	High	Medium large
High	Low	Rather large
High	Medium	Large
High	High	Very large

Fuzzy rules for global level:

Centrality	Proximity to BS	Distance between CHs	Qualification in global level
Low	Low	Low	Large
Low	Low	Medium	Very large
Low	Low	High	Very large
Low	Medium	Low	Rather large
Low	Medium	Medium	Large
Low	Medium	High	Large

(*continued*)

Continued.

Centrality	Proximity to BS	Distance between CHs	Qualification in global level
Low	High	Low	Medium large
Low	High	Medium	Rather large
Low	High	High	Rather large
Medium	Low	Low	Medium
Medium	Low	Medium	Medium large
Medium	Low	High	Medium large
Medium	Medium	Low	Medium small
Medium	Medium	Medium	Medium
Medium	Medium	High	Medium
Medium	High	Low	Rather small
Medium	High	Medium	Medium small
Medium	High	High	Medium small
High	Low	Low	Small
High	Low	Medium	Rather small
High	Low	High	Rather small
High	Medium	Low	Very small
High	Medium	Medium	Small
High	Medium	High	Small
High	High	Low	Very small

3.4. *Fuzzy C-mean*

FCM (Fuzzy *C*-mean) is a centralised clustering technique which uses the location information of nodes and the highest residual energy for selecting cluster heads. It assigns a degree of belonging to each node for each cluster head rather than completely being a member of just one cluster. Then after the cluster formation is done by minimising an objective function comprised of degree of belongingness and the distance between the node and centre point of the cluster. The fuzzy logic principles are used for fuzzifying the degree of belongingness after it has been calculated, using the function defined therein, which ensures better optimisation in cluster formation. After first stage of clustering and data transmission, the current cluster heads choose a new cluster head for next stage depending upon the energy level received from each node as piggybacking information in each packet received from the node. There is better formation of clusters as compared to other approaches because mean distance of each node to cluster head is minimised which in turn optimises the transmission power of non-cluster head nodes (Hoang, Kumar, and Panda 2010). The model is also compared with LEACH and *K*-means clustering. Simulation results show that this method reduces energy consumption and improve the lifetime.

Figure 5 is generated using FCM approach which shows that it gives clusters of almost same size as compared to probabilistic approach mentioned in Figure 4. In this way fuzzy *C*-means approach is more useful to distribute the load of the network and to distribute the nodes among the clusters.

3.5. *F3N algorithm*

Three versions of F3N are available in Ando, Barolli, Durresi, Xhafa, and Koyama (2010a, b) and Barolli et al. 2011 which have minor differences. It uses fuzzy logic and

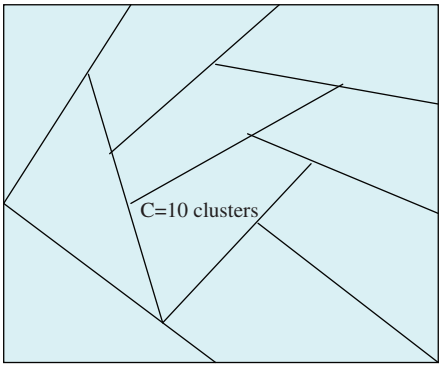

Figure 5. Cluster formation in FCM approach.

number of neighbour nodes (thus called F3N) along with other parameters for clustering purpose. The authors argue that the selection of cluster head is difficult in different environment having different characteristics but proper use of fuzzy logic can improve the performance. Three parameters are considered in F3N scheme; (i) distance from cluster centroid (DCC), (ii) degree of number of neighbour nodes (D3N) and (iii) remaining battery power of sensor (RPS). Three fuzzy subsets have been chosen for above three parameters. For remaining battery power subsets are low, medium and high. For D3N fuzzy subsets are few, medium and many. For DCC parameter three subsets are light, moderate and heavy. In this scheme output is possibility of cluster head selection (PCHS). For output, i.e. PCHS term sets are: very weak (VW), weak (W), little weak (LW), medium (MD), little strong (LS), strong (S) and very strong (VS). Simulation results of this scheme show that the possibility of a sensor node to be a cluster head increases with decrease of distance from the centroid, as well as with the increase in the residual battery energy and number of neighbour nodes. This study has been further extended by same group of authors. Another parameter, network traffic (NT), has been included and it has been claimed to show better results (Ando et al. 2011).

Fuzzy rules for F3N algorithm:

RPS	D3N	DCC	PCHS
Low	Few	Light	VW
Low	Few	Moderate	W
Low	Few	Heavy	W
Low	Medium	Light	W
Low	Medium	Moderate	W
Low	Medium	Heavy	W
Low	Many	Light	VW
Low	Many	Moderate	VW
Low	Many	Heavy	VW
Medium	Few	Light	W
Medium	Few	Moderate	LW
Medium	Few	Heavy	M
Medium	Medium	Light	LW
Medium	Medium	Moderate	MD

(*continued*)

Continued.

RPS	D3N	DCC	PCHS
Medium	Medium	Heavy	LS
Medium	Many	Light	MD
Medium	Many	Moderate	LS
Medium	Many	Heavy	S
High	Few	Light	LW
High	Few	Moderate	M
High	Few	Heavy	LS
High	Medium	Light	MD
High	Medium	Moderate	LS
High	Medium	Heavy	S
High	Many	Light	LS
High	Many	Moderate	S
High	Many	Heavy	VS

3.6. *Fuzzy self clustering algorithm*

Fuzzy self clustering algorithm (FSCA) scheme improves the performance of ACE (an emergent algorithm for highly uniform cluster formation) clustering technique by replacing its exponential functions by fuzzy logic based system in each node. FSCA ensures the uniform clusters without categorically specifying the nodes eligibility to become a cluster head. It is especially useful when all the nodes within a cluster possess low energy. Node residual energy, local density within its sensing range, and time is considered by two fuzzy logic modules. In first iteration, the clusters are formed with size equal to or greater than the network density then after these clusters migrate away from each other such that the overlap between them is reduced to zero. New clusters might be formed in this process. The fuzzy modules play dominant role in the entire process which are much efficient than the complex procedure what is required to be used otherwise (Tashtoush and Okour 2008).

Initiation rules:

Node's time (t)	Node's loyal follower	Initiation chance
Low	Low, medium	0
Low	High	1
Medium	Low	0
Medium	Medium, high	1
High	Low, medium, high	1

Migration rules:

Node's loyal followers	Node's energy	Migration chance
Low	Low, medium, high	1, 2, 3
Medium	Low, medium, high	4, 5, 6
High	Low, medium, high	7, 8, 9

3.7. *Neuro-fuzzy technique*

The memory, available power, processing speed, etc. parameters are collected and fuzzified for generating the monitoring coefficients for each node. These coefficients are then supplied to Kohonen Self Organisation Map Neural Network, which does the clustering. It does not need the location information thus works pretty good in dense environment too (Veena and Vijaya Kumar 2010).

Fuzzy rules:

Power	Memory	Processing speed	Monitoring coefficient
Low	Low	Low	Not used
Medium	Medium	Medium	Critical
Medium	High	Medium	Event
Medium	Medium	High	Event
Medium	High	High	Event
High	High	Medium	Continuous
High	Medium	High	Continuous
High	High	High	Continuous

3.8. *Cluster adaptation method*

It is targeted towards better routing in clustered network. The statistical en-route filtering (SEF) has been identified to perform poorly if each possible feature is not accounted. The performance improvement in SEF has been reported by developing a fuzzy logic based system. It evaluates the fitness of the cluster by getting four parameters, namely, partition information of cluster region (PICR), distance from cluster head to base station (DFC), the energy of cluster head (EOC) and the number of sensor nodes in cluster region (NSCR). Significant improvement in the correct event reports has been observed (Kim, Moon, Lee, Sun, and Cho 2009).

Fuzzy rules to determine fitness of the cluster with a cluster head (CFWC):

PICR	EOC	DFC	NSCR	CFWC
Not need	Low	Near	Very few	Stop
Not need	Low	Middle	Few	Stop
Need	Middle	Middle	Enough	Stop
Need	Low	Near	Very few	Stop
Need	Low	Middle	Very many	Consider
Need	Low	Near	Very few	Stop
Need	Middle	Near	Very few	Consider
Need	Middle	Away	Few	Move
Need	Enough	Middle	Enough	Move
Need	Enough	Away	Very many	Move

3.9. *Fuzzy unequal clustering algorithm*

Fuzzy unequal clustering algorithm (EAUCF) is primarily addressing the problem of hot spots in multi-hop WSNs. Most of the clustering methods do not consider the position of sink thus hot spots occurs in the region close to the sink. EAUCF adjusts the cluster

head radius by considering residual energy and distance from base station. Fuzzy logic model is used for handling the uncertainties in competition range estimation (Bagci and Yazici 2010). Following is the rule base table for this algorithm.

Distance to base	Residual energy	Competition radius
Close	Low	Very small
Close	Medium	Small
Close	High	Rather small
Medium	Low	Medium small
Medium	Medium	Medium
Medium	High	Medium large
Far	Low	Rather large
Far	Medium	Large
Far	High	Very large

3.10. *Other techniques*

In Anno, Barolli, Xhafa, and Durresi (2007), distance of cluster centroid, remaining battery power of the sensor node and NT have been given as input to the fuzzy logic based model which gives the PCHS as the output. It has been reported that the remained battery power of sensor node is more important for cluster head selection than NT. With the increase in the NT and increase of the distance between sensor and sink, possibility of node to be selected as a cluster head decreases.

Another fuzzy logic based model has been proposed in Gupta, Riordan, and Sampalli (2005). It needs three input parameters namely energy, concentration and centrality for finding the suitable cluster head. Simulation results show that it is best suited for medium sized clusters, for which the performance is much better than probabilistic approach.

4. Comparison of surveyed algorithms

Hereunder in Table 1 a comparative analysis of various surveyed algorithms has been presented.

Table 1. Comparative analysis of fuzzy based algorithms for cluster head election.

Algorithm	Details of fuzzy model used in the algorithm	Key features
NECHS	*Fuzzy logic type* • Type-1 fuzzy set *Input parameters* • Neighbour nodes • Node residual energy *Output parameter* • Probability of cluster head selection *Membership function for input parameters* *for neighbour node* Trapezoidal-few, many Triangular-medium	• More efficient than LEACH • If node energy is low or very low, it will obtain a low probability to be a cluster head based on the fuzzy logic rules

(*continued*)

Table 1. Continued.

Algorithm	Details of fuzzy model used in the algorithm	Key features
	For Node residual energy Trapezoidal-very low, high Triangular-low middle *Membership function for output parameter* *for probability* Trapezoidal-very low, very high Triangular-low, little low, medium, little high, high	
CHEF	*Fuzzy logic type* Type-1 fuzzy set *Input parameters* • Energy • Local distance *Output parameter* Chance to cluster head selection *Membership function for input parameters* *for energy* Trapezoidal-low, high Triangular-medium For local distance Trapezoidal-close, far Triangular-medium *Membership function for output parameter* Triangular	• More efficient than LEACH • Not based on probability model like LEACH CHEF is 22.7% more efficient than leach
Two-level fuzzy logic	*Fuzzy logic type* Type-1 fuzzy set at two level *Input parameters at local level* • Node energy • Local distance *Output parameter at local level* Qualification of node for cluster head *Input parameters at global level* • Centrality • Proximity to base station • Distance between CHs *Output parameter at global level* • Qualification of node for cluster head *Membership function for input parameters* *for energy* Trapezoidal-low, high Triangular-medium *For number of neighbours* Trapezoidal-low, high Triangular-medium *For centrality* Trapezoidal-low, high	• Fair load distribution • Fewer variance of energy consumption • Algorithm improve overall lifetime about 54%

(*continued*)

Table 1. Continued.

Algorithm	Details of fuzzy model used in the algorithm	Key features
	Triangular-medium *For proximity to base station* Trapezoidal-low, high Triangular-medium *For distance between CHs* Trapezoidal-low, high Triangular-medium *Membership function for output parameter* Triangular	
FCM	*Fuzzy logic type* Type-1 fuzzy Set Mean distance of each node to cluster head	• Uniform clusters • Better lifetime
F3N	*Fuzzy logic type* Type-1 fuzzy set *Input parameters* • DCC • D3N • RPS *Output parameter* • Probability of CH selection *Membership function for input parameters* *for DCC* Trapezoidal-light, heavy Triangular-moderate *For D3N* Trapezoidal-few, many Triangular-medium *For RPS* Trapezoidal-low, high Triangular-medium *Membership function for output parameter* Triangular	• More efficient than LEACH • Lesser consumption of energy • Probability of a sensor node to be a cluster head is increased with increase of number of neighbour nodes and remained battery power and decrease of distance from the cluster centroid
FSCA	*Fuzzy logic type* Type-1 fuzzy set *Input parameters for initiation fuzzy module (IFM)* • The node lifetime • Node's total number of loyal followers *Output parameter* Chance to being cluster head *Input parameters for migration fuzzy logic module* • Node's loyal followers • The reserved power	• Reduce overlap area between cluster • Reduce amount of redundant messages originated from clusters that cover the same sensing area • FSCA increase the network lifetime by uniformly distributing the clusters • Provide efficient coverage

(*continued*)

Table 1. Continued.

Algorithm	Details of fuzzy model used in the algorithm	Key features
	Output parameter • Chance of being the new cluster-head *Membership function for input and output parameter* Triangular	
Neuro-fuzzy technique	*Fuzzy logic type* Type-1 Fuzzy set *Input parameters* • Memory • Available power • Processing speed *Output parameter* Monitoring coefficients *Membership function for input parameters:* *for memory* Trapezoidal-low, high Triangular-medium *For available power* Trapezoidal-low, high Triangular-medium *For processing speed* Trapezoidal-low, high Triangular-medium *Membership function for output parameter* Trapezoidal-not used, continuous Triangular-critical, event	• Result used in various application like low energy cluster would be used for event based monitoring applications • High-energy cluster can be used in continuous monitoring system
Cluster adaptation method	*Fuzzy logic type* Type-1 fuzzy Set *Input parameters* • PICR • DFC • EOC • NSCR *Output parameter* CFWC *Membership function for input parameters* *For PICR* Triangular- not need, need *For EOC* Trapezoidal-low, enough Triangular-middle *For NSCR* Triangular *Membership function for output parameter:* Triangular	• A fuzzy rule based system has been exploited to evaluate the fitness of the clustering adaptation

(*continued*)

Table 1. Continued.

Algorithm	Details of fuzzy model used in the algorithm	Key features
EAUCF	*Fuzzy logic type* Type-1 fuzzy Set *Input parameters* • Distance to base • Residual energy *Output parameter* • Competition radius *Membership function for input parameters:* *for distance to base* Trapezoidal-close, far Triangular-medium *For residual energy* Trapezoidal-low, high Triangular-medium *Membership function for output parameter* Triangular	• Prolong the lifetime of the WSN by evenly distributing the workload • More efficient than LEACH, CHEF. • EAUCF adjusts the cluster-head radius

5. Conclusion

Clustering is a very important operation in several applications of WSN but it is not the main job of the WSN. It must ensure a prolonged lifetime of WSN, at the same time it should itself not consume too much energy. Fuzzy logic based clustering techniques have the potential to form optimised clusters such that the overall energy consumption in operation phase is brought down. Realising this fact, several researchers are working since past few years, towards development of an effective fuzzy logic based clustering algorithm for WSN. The approach adopted by them, the models developed and the results obtained have been summarised in this study. A comparative table is prepared for easy glancing the merits and drawbacks of the available techniques. Yet, no technique is enough perfect for adopting it for commercial purposes. It is still an open challenge for further research and development.

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