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Bio-inspired routing protocol for wireless sensor network to minimise the energy consumption

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Abstract: The minimisation of energy consumption has become an emerging topic in wireless sensor networks (WSNs) as these networks enable a wealth of new applications. The internet of things (IoT) application is one of them and the current hype around the IoT is huge. Therefore, the development of efficient communication protocols for WSNs is a major concern. In this context, various research communities have triggered several optimisation techniques to provide energy-efficient solutions to WSNs. This study aims to apply the genetic algorithm (GA) in WSNs clustering and to evaluate its performance over another optimisation technique. The proposed protocol is analytically analysed and compared with a fuzzy logic (FL)-based routing protocol and traditional routing protocol like LEACH and *K*-means using a Java-based custom simulator. Simulation results show that there is a trade-off between GA-clustering and FL-clustering, but the overall performance of GA-clustering is very promising for obtaining optimal energy consumption.

1 Introduction

Rapid growth in the field of internet of things (IoT) along with wireless communication has led to the development of tiny, smart sensor nodes those play a major role in implementing IoT. It facilitates billions of devices to share the data by their sensing and communicating capability. It seems like every day a new company announces some IoT-enabled product. Wireless sensor network (WSN) consists of hundreds or thousands of sensor nodes organised in an *ad hoc* pattern to observe and interact with the physical world. Each sensor node consists of four elements; sensing unit, processing and storage unit, power supply and transceivers. The sensing unit is responsible for measuring the physical parameters in the real world such as temperature, pressure, humidity, acoustic signal, vibrations, vehicular movements etc. [1]. These sensed values are handled by the processing unit and forwarded to the base station (BS) through intermediate nodes either by single-hop or multi-hop fashion. Energy consumption, limited bandwidth and limited memory is the main challenging issue in designing a protocol in WSN. Most of the time the sensor networks are deployed in unattended terrain, where recharging and replacement of battery is quite impossible. Despite of enormous constraints, the applications of WSNs are huge in range that vary from military surveillance to health-care monitoring, agriculture, inventory control, industrial automation etc. The basic architectural model of WSN is shown in Fig. 1.

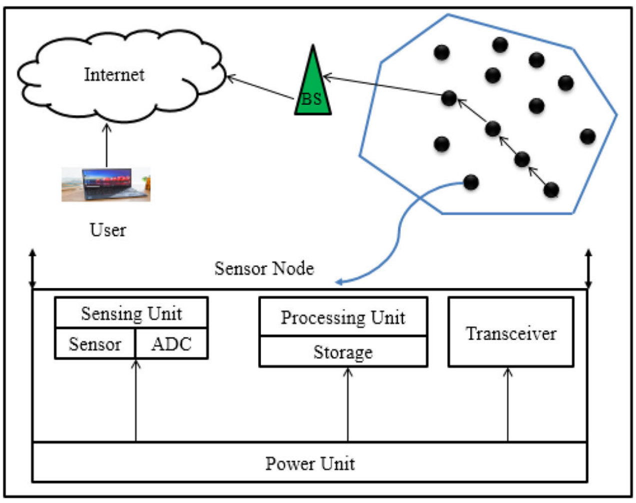

Fig. 1 *Basic structure of WSN*

Many researchers have put their effort into designing routing protocols for WSN since last decade and proved their energy efficiency through simulation results [1–14]. Clustering-based routing technique is one of these efficient techniques, where the whole sensor network is partitioned into small size networks (clusters) to resolve the scalability issue of the network. In these networks, each cluster is controlled by an efficient node known as cluster head (CH). Whenever any event occurs, all the sensor nodes inside a cluster send the sensed data to the respective CHs. These CHs aggregate the sensed data and send it to the BS either directly or through the other CHs till it reaches the BS. The objective of the clustered-based routing protocol (equal or unequal) is purely application specific. However, the overall target is to minimise energy conservation and to overcome hot spot problems. Some of the added features which cannot be compromised are discussed below.

- *Scalability*: sensor nodes are deployed in large numbers that range from hundreds to thousands of nodes depending on the requirement of the applications in real time scenario. When the sensor nodes are large, clustered-based routing can only provide scalability in large scale by dividing the sensor field into number of levels and dividing each level into number of clusters.
- *Data aggregation/fusion*: data fusion occurs at BS level, but in clustering-based algorithm local data fusion occurs at CH level and global data fusion occurs at BS level.
- *Load balancing*: rotation of CH among all the sensor nodes is required within a cluster in order to balance the network load. Proper selection of CH must be taken care of to accomplish the objectives.
- *Fault tolerant*: as sensor networks are deployed in an open environment without human monitoring system, it must be robust enough to handle the changes in physical properties of ever-changing environment.
- *Stable network topology*: stable network topology is an essential feature to minimise the energy consumption.
- *Increased lifetime*: energy conservation is the major concern in WSN that directly lengthens the network lifetime. So, proper

cluster formation and selection of efficient CH is an important phenomenon in designing a routing protocol in WSN.

Motivation: In practical sensor field, it's hard to apply optimisation techniques directly as it takes a long time to satisfy rapidly evolving applications and requirements due to limited power supply, low transmitting capacity, low data rate and short-range communication. All these constraints in WSN affect the overall performance of the network and restrict their future potential utilisations to improve the system performance. In contrast, focus on software aspects (design of energy-aware protocols, the development of specific communication strategies or the enhancement on existing protocols) can provide a quick solution for performance optimisation by selecting a few performance metrics. The commonly accepted methods of evaluating the above solutions before deploying in real time scenario can be checked through software modelling. It could be theoretical model and simulation or real-world testbed experiments. Theoretical models are faster to evaluate compared with software-based simulations, but sometimes idealised and inaccurate for realistic conditions. Therefore, simulation is considered as a more suitable trade-off between efficiency and accuracy.

Further, real time and new proposed problems are going to be more complex in terms of scalability and other aspects of non-linearity. Increasing complexity of problems require more information whereas fuzzy logic (FL) performs well by applying linguistic rules without having the detailed knowledge of controlled system. On the other hand, the optimisation techniques like genetic algorithm (GA), the designer cannot regulate the performance without acquiring the detailed information of the proposed system. These two optimisation techniques are well established and widely used in many areas of Science and Engineering. So, the aim of this proposed work is to develop a GA-based clustering algorithm for WSN and to compare the performance with a FL-based clustering algorithm proposed in [15] and to analyse the impact on WSNs. LEACH and *K*-means is also taken as a reference as these algorithms are the basic building blocks and provide a platform to design and improve the system performance.

The rest of the study is structured as follows. Section 2 presents an overview of the clustering techniques in WSN. Section 3 discusses the radio model and Section 4 presents the proposed algorithm. The experimental results are discussed in Section 5 followed by concluding remark in Section 6.

2 Related work

This section discusses few clustered-based routing protocols where the CHs are elected in rotation basis. We have selected few existing algorithms from the current literature according to our choice of interest to compare with the proposed GA-based clustering algorithm.

2.1 Clustering techniques used in probabilistic model

LEACH [1] is the first hierarchical routing protocol that follows a probabilistic model to elect the CH demanding that each sensor gets equal chance to become a CH. It operates on two phases; steady state phase and set-up phase. The steady state phase takes care of nodes to form a cluster and the set-up phase allows the nodes to transmit the data to the BS. Each node opts a random number between 0 and 1. If the number lies below the threshold value $T(n)$, the node becomes the CH for the current round. The threshold value $T(n)$ is stated in (1).

$$T(n) = \begin{cases} \dfrac{p}{1 - p * \left(r \bmod \dfrac{1}{p}\right)}, & \text{if } n \in G \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

r is the completed round, p is the probability of the nodes to become CH, G is a set of nodes those have never got a chance to be CH in the last $1/p$ rounds. Although LEACH provides support for load balancing, still it has many drawbacks. One may refer [16, 17] for more information. LEACH-C [2] is the modified version of LEACH which elects the BS follows the principle of centralised concept. Many clustering protocols with pros and cons have been discussed in [3–8, 13]. In [18], a mathematical framework is discussed for obtaining optimal number of clusters by considering noisy WSN environment.

2.2 K-means clustering

K-means is an unsupervised learning algorithm, initially used for data clustering proposed by MacQueen in 1967. It partitions the data set into certain number of clusters using the Euclidian distance mean, that maximises the intra-cluster similarities and minimising the inter-cluster similarities. It generates arbitrarily k points (centre of the clusters), k being the desired number of clusters. The distance between each of the data points to each of the centres is calculated and assigned each point to the closest centre. The centre of the new cluster is calculated by the mean value of all data points in the respective cluster. The distance between the data points is calculated using Euclidean distance defined by (2) given below

$$E = \sum_{i-1}^{k} \sum_{x \in C_i} |X - \overline{X_i}|^2 \quad (2)$$

Few researchers [10–12] have proposed some clustering techniques based on *K*-means or little variations of *K*-means clustering and proved their efficiency. In our work, we have used the basic model of *K*-means clustering as discussed in the above paragraph.

2.3 Fuzzy logic-based clustering protocol

The precise quantification of many system performance and parameters is not always possible, not required also. In any system, when the variables cannot be precisely computed, they are called as fuzzy or uncertain. If the values are uncertain, probabilistic distribution function may be used to quantify them. If the variables are best described by the computational adjectives, fuzzy membership functions are used to describe them. Few studies discuss the application of FL in WSN routing [15–17, 19–21]. The research in [15] discusses the advantages of T2FL (interval type) over T1FL [17] clarifying that the membership degrees of T2FL are themselves fuzzy set. So, we have considered [15] to compare the performance of our proposed GA-based protocol. One may refer [15] for the detailed information.

2.4 Genetic algorithm-based clustering protocol

GA is a bioinspired algorithm, mainly aims to provide near optimal solutions for any computational problem. Many different approaches are discussed in [14, 22–25] how GA could be productive in clustering for WSN so that it can balance the load among the sensor nodes to lengthen the network lifetime. This section presents few GA-based routing protocols. In [14], a GA-based routing approach is proposed in two-tiered sensor networks that maximises the network lifetime by consuming optimal energy. In [26], a flat based routing is discussed that uses MOGA [24] to find paths in a WSN. Research in [22] shows an improved lifetime of a multi-sensor networks through optimal traffic distribution technique. The work of [23] focuses on GA that calculates the fitness function on the basis of distance, hop count and energy and is proved as energy efficient. The drawback of the proposed algorithm is slow execution. In [25], the author has focused on chain-based routing technique PEGASIS as basis and follows GA procedure to build the chain instead of greedy algorithm. Even though the proposed algorithm proves its efficiency in terms of load balancing, residual energy and delay, it has few drawbacks. Weights of the CHs are selected randomly. Each chain is built up separately after clustering. In [27], the author has discussed a GA-based clustering that increases the network lifetime over basic LEACH and GCA, but the disadvantage of the algorithm is that one must adjust the weight co-efficient every time to achieve better performance.

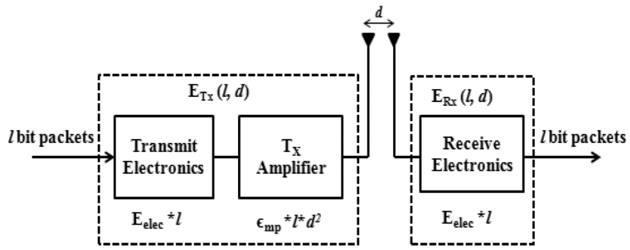

Fig. 2 *Radio model*

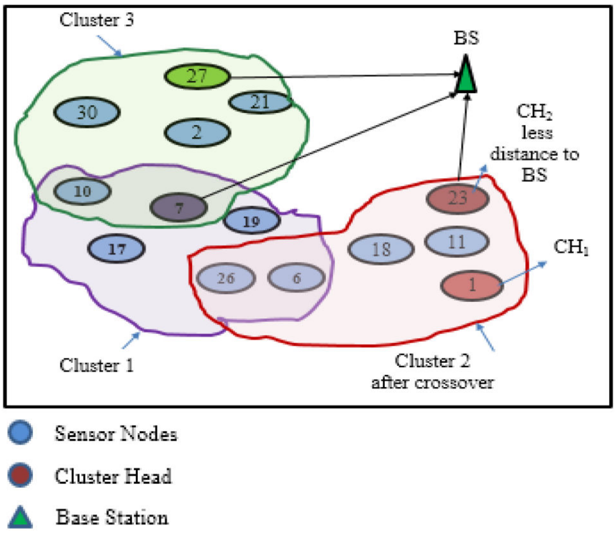

Fig. 3 *Proposed model*

Even though several comprehensive studies on clustering are demonstrated potentially, very few have discussed on dynamic clustering using GA. We found that the clarity of GA steps incorporating clustering in WSN is lagging in the current literature. The absence of clarity inspired us to design a GA-based clustering algorithm expecting that it can lead to optimal energy consumption. The proposed protocol supports to form the cluster dynamically and to select an efficient CH based on the highest residual energy and lowest distance to BS. Further, as discussed above, many studies discuss the efficiency of FL for optimal energy consumption in WSN. So, out of curiosity, to check the performance of both the optimisation techniques in WSN, we proposed a routing technique based on GA. The following sections describe the working principle of the proposed heuristic in detail.

3 Energy model analysis

The first order radio model referred from [19] is shown in Fig. 2. The total energy consumption to transmit/bits over a distance d from a transmitter to receiver is given below

$$E_{Tx}(l, d) = E_{Tx-elec}(l) + E_{Tx-amp}(l, d)$$
$$= \begin{cases} l * E_{elec} + l * \varepsilon_{fs} * d^2 \text{ if } d < d_0; \\ l * E_{elec} + l * \varepsilon_{mp} * d^4 \text{ if } d \geq d_0; \end{cases} \quad (3)$$

- E_{elec} denotes the energy dissipated per bit to run the transmitter or the receiver circuit. It mostly depends on the parameters like digital coding, modulation, filtering and spreading of the signal.
- ε_{fs} & ε_{mp} are the characteristics of the transmitter amplifier where ε_{fs} is meant for free space and ε_{mp} meant for multipath.

When the threshold value d_0 is greater than the distance between transmitter and receiver, the free space model (d^2 power loss) is employed. Otherwise, the multipath fading channel model (d^4 power loss) is used. Power amplifier can be adjusted appropriately to invert this loss. The amount of energy consumption to receive l bit of data and the threshold value which is the ratio of ε_{fs} & ε_{mp} is given in (4) and (5), respectively

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

$$d_0 = \sqrt{\varepsilon_{fs}/\varepsilon_{mp}} \quad (5)$$

4 Proposed heuristic

Typically, the GA operators such as selection, crossover and mutation process run till the new populations (offsprings) appear like the initial population. Only then, it is concluded that the second generation is formed entirely of new population and the first generation is completely substituted.

4.1 System assumption for proposed heuristic

In our proposed model which is shown in Fig. 3, sensor nodes are deployed randomly to observe the environment continuously.

(i) All the sensor nodes are static.
(ii) BS is also static.
(iii) Network is considered as homogeneous such as all the sensor nodes have initial equal energy.
(iv) Received signal strength is the indicator for measuring the distance between sensor node and BS.

4.2 Procedure for GA clustering

/ for every round */*
Apply binary encoding to perform GA operation
Apply GA to select $k_{optimal}$ CHs in each round.
{Procedure for GA}

- Initialise the population
- Create the chromosome list through binary encoding)
- Randomly select few chromosomes
- Calculate the fitness function using (6)
- Perform the crossover and mutation operation to create new population
- new population implies the offsprings)
- Create the cluster taking new population
- Select the CH from the new cluster based on the fitness value
- If more than one sensor node is selected as CH in the same round (due to same energy level), one node can be selected as CH based on lowest distance to BS
- Finally, the node is having higher energy and less distance to BS is selected as CH in that round

/ for $k_{optimal}$ CHs */*
All CHs send the aggregated data to BS
/ end of for */*
BS gathers the aggregated data and takes a higher-level decision
/ end of rounds */*

4.3 Genetic algorithm model

The step by step operations of GA incorporated in our work are given below.

(i) *Encoding*: in our proposed work, we have considered binary encoding justifying that the sensor nodes can be classified into two categories; normal sensor node and CH node. Senor node can be represented as a gene that implies (0) and CH can be represented as a gene that tends to (1) to generate the chromosome.
(ii) *Initial population*: the length of the chromosome is decided based upon the number of nodes. Here, we have considered the length of chromosome as 6. So, ($2^6 = 64$) initial chromosomes can be created. Fig. 4 shows the chromosome structures in detail. Length of the chromosome can be increased to any number, but the

chromosome length is restricted to 6 here, due to space constraints and easy explanations.

(iii) *Evaluation of fitness function*: in the proposed approach, the fitness function of a chromosome in the population is calculated by considering the ratio of the remaining energy to initial energy of a sensor node as defined in

$$f_{\mathrm{t}}(x) = \frac{E_{\mathrm{r}}}{E_{\mathrm{i}}} \tag{6}$$

E_{r} = remaining energy of a sensor node after each round, E_{i} = initial energy of a sensor node

(iv) *Selection operator*: in this work, Elitism selection method is used. We have used probability density function for selecting the node to be the CH as provided in 7.

(v) *Crossover operation*: crossover and mutation are the two basic operators of GA. Fig. 4 shows the initial chromosome structure. We have randomly selected six chromosomes to perform GA operations. The fitness function is calculated using the formula given in 6. Table 1 shows the initial population and calculated fitness value without performing crossover. Fig. 5 shows the new population after performing the crossover operation. We have checked the result performing single point as well as multi point crossover operation. The idea is to find an efficient CH, with the probability of being one node as CH so that network load can be properly distributed.

(vi) *Mutation*: to replicate the mutation operation in proposed GA clustering, the mutation rate r is considered as 0.001, which is very low. If r is 0.001, mutation probability in our case $0.001 \times 512 = 0.512$. It looks like that a slight chance of mutation to occur in the second generation. For sake of demonstration, we have mutated one bit which is presented in Fig. 6.

Here, we select the chromosome that will be the CH based on their fitness value, using the following probability.

$$P\,(\text{Chromosome i of being CH}) = \frac{(f x_{\mathrm{i}})}{\sum_{m=1}^{n} f(x_{\mathrm{m}})} \tag{7}$$

For Instance; $P(C_{10}) = 0.695/4.03 = 0.17$

4.4 Description of proposed algorithm

The idea of incorporating GA in WSN routing is that GA can help to formulate the optimal number of clusters and we can select an efficient CH based on the fitness value. By doing so, it activates the system to save some amount of energy that can directly lengthen the network lifetime. The length of the chromosome is considered as 9. So, $2^9 = 512$ chromosomes are created as the initial population using binary encoding. Out of 64 chromosomes, six chromosomes are selected randomly for demonstration. After selecting the chromosomes, crossover and mutation operations are performed to create the new population. Single point crossover is considered to create the new population for the sake of simplicity. The result is shown in Figs. 5 and 6. Elitism selection method is used. Fitness function is calculated based on the ratio of residual energy to initial energy of a sensor node as defined in (6). Probability of being CH is calculated using the formula stated in (7). In new population, the node is having the highest residual energy is selected as CH. Always there is a probability of more than one sensor node having equal residual energy. To avoid this conflict, we have calculated the distance to BS as given in (8). The selected CHs having more or equal residual energy with minimal distance to the BS is selected as CH.

$$T_{\mathrm{d}} = T_{\mathrm{d1}(s-\mathrm{ch})} + T_{\mathrm{d2}}(\mathrm{ch}-\mathrm{bs}) \tag{8}$$

T_{d} = total communication distance from sensor node to BS via CH, $T_{\mathrm{d1}\,(s-\mathrm{ch})}$ = distance from sensor node to CH, $T_{\mathrm{d2}}\,(\mathrm{ch}-\mathrm{bs})$ = distance from CH to BS

Chromosome Number	Initial Population
1	0 0 0 0 0 0 0 0 1
2	0 0 0 0 0 0 0 0 1
3	0 0 0 0 0 0 0 1 1
4	0 0 0 0 0 0 1 0 0
5	0 0 0 0 0 0 1 0 1
6	0 0 0 0 0 0 1 1 0
. . 512	1 0 0 0 0 0 0 0 0 0

Fig. 4 *Generation of initial population*

Table 1 Fitness value without crossover

Sl. No	Initial population	(Node ID) *X* value	Fitness value *f*(*x*)	Prob. of being CH
1	000001010	10	695/1000 = 0.695	0.17
2	000000110	6	5/1000 = 0.005	0.001
3	000010001	17	915/1000 = 0.915	0.22
4	000000111	7	695/1000 = 0.695	0.17
5	000011010	26	805/1000 = 0.805	0.19
6	000010011	19	915/1000 = 0.915	0.22
			Sum = 4.03	

Sl No	Initial Population	Mating Point	New Population	X Value	Fitness Value f(x)
1 6	000001010 000010011	00000|1010 00001|0011	000000 011 000011 010	3 26	695/1000 =0.695 255/1000 =0.255
2 5	000000110 000011010	000000|110 000011|010	000000 010 000011 110	2 29	805/1000 =0.805 5/1000 =0. 005
3 4	000010001 000000111	00001|0001 00000 0111	000010 111 000000 001	23 1	915/1000 = 0.915 915/100 = 0.915

Fig. 5 *Creation of new population after crossover*

5 Performance evaluation

In this Section, we have discussed about the experimental set up and simulation results of our proposed algorithm in detail.

5.1 Simulation settings

To check the validity of the proposed protocol, we have used a Java-based custom simulator. The simulation parameters are defined in Table 2. We have created a sensor field of 512 nodes geographically placed at a terrain of 250 m × 250 m. For the sake of clear demonstration, 500 nodes are taken for plotting the simulation results. Packet size is considered as 4 bytes. We have considered for 40 rounds. The duration of each round is 50 ms.

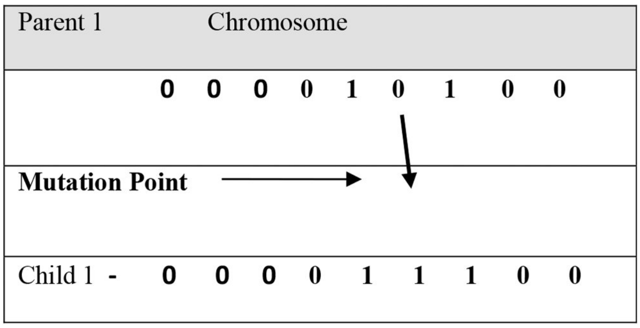

Fig. 6 *Mutation operation*

Table 2 Simulation parameters

number of sensor nodes	500
area of sensor field	250 m × 250 m
simulation time	2000 ms
transmission range	8 cm
data rate	64 bytes/s
packet size	4 bytes
initial energy of a sensor node	1000 J
initial energy of BS	10,00,000 J
population length	9
number of generations	20
number of rounds	40
crossover rate	0.5
crossover type	single point
communication model	bi-directional

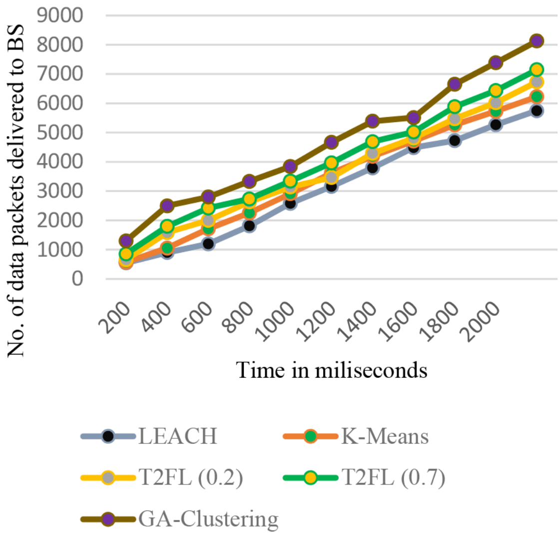

Fig. 7 *No. of data packets delivered to BS versus time*

Uniform crossover is considered having crossover rate 0.5. After extensive simulations, the new findings are plotted from Figs. 7–12.

5.2 Evaluation metrics

Few important metrics are chosen to evaluate the efficiency of the proposed protocol which are discussed below.

- *No. of data packets delivered to BS*: this is the main parameter to measure the performance of any type of communication protocol. The aim of any routing protocol is to deliver maximum number of data packets at the destination. So, the ratio of data packets delivered to BS to the number of data packets sent by the source node gives a measure of packet delivery ratio. Fig. 7 shows the comparison result of our proposed protocol with Type 2 FL (T2FL), LEACH and *K*-means clustering. As the membership function of T2FL is itself fuzzy and contains a range from 0 to 1, we have taken 0.2 for lower range and 0.7 for upper range to measure the performance. It is evident from Fig. 7 that the no. of data signals delivered to BS is more in GA-clustering compared to T2FL clustering, LEACH and *K*-means.

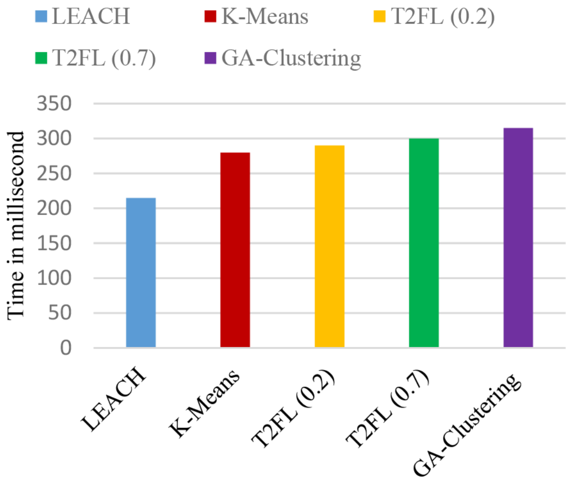

Fig. 8 *First node dies over time*

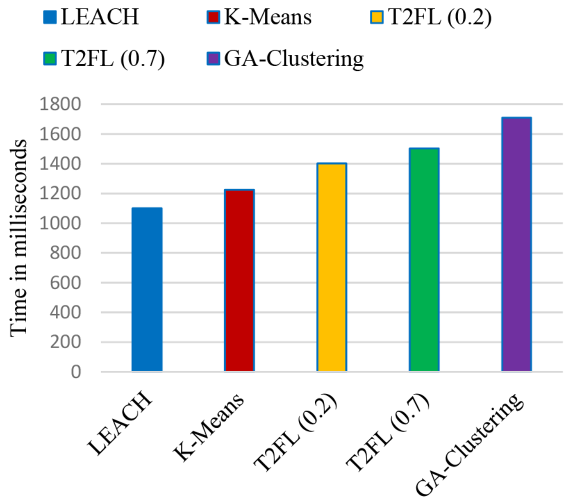

Fig. 9 *Half nodes die over time (N/W stable period)*

- *First node dies*: it defines the time when the whole energy is depleted in a sensor node. From our experiment, it is concluded that the first node dies at 210 ms in LEACH, it happens at 275 ms for *K*-means, at 300 ms in T2FL but it happens at 315 ms for proposed GA-clustering. The results are plotted in Fig. 8.
- *Half nodes die*: it conveys the stable period of the sensor network. In our experiment, half of the nodes die in LEACH first (at 1100 ms), followed by *K*-means (at 1200 ms) and T2FL clustering (at 1400 ms), but in GA- clustering 50% of nodes sustain for >1700 ms as shown in Fig. 9. The unstable period of a network starts after the death of 50% nodes. Slowly performance of the network degrades.
- *Average energy consumption*: the average energy consumption of these three protocols is plotted in Fig. 10. It is seen that average energy consumption is more in LEACH, moderate in *K*-means followed by T2FL clustering and GA-clustering. Even though GA-clustering delivers a greater number of packets to the BS compared to other discussed algorithms, the average energy consumption is less in GA-clustering. It justifies that the energy consumption takes place evenly among all the sensor nodes and all over the network that leads the network to sustain for longer period.
- *Scalability*: to solve the scalability issue, we increased the number of nodes to 500 and we found that a greater number of clusters are formed in T2FL initially, but as the time increases better no. of clusters are formed in GA-clustering compared to

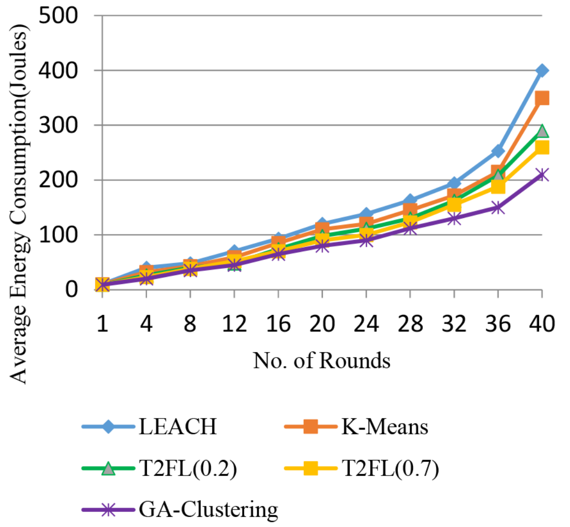

Fig. 10 *Average energy consumption versus No. of rounds*

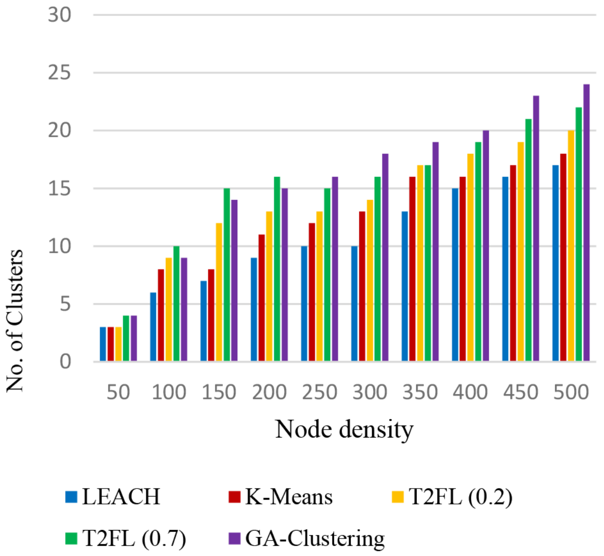

Fig. 11 *Node density versus No. of clusters*

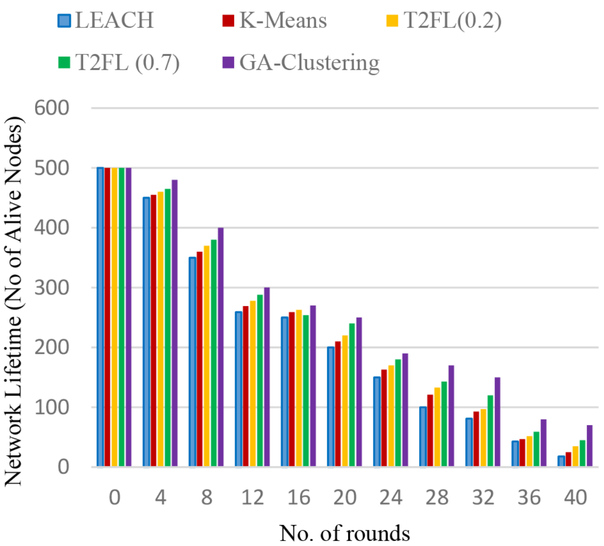

Fig. 12 *Network lifetime w.r.t no. of alive nodes*

T2FL, LEACH and *K*-means as shown in Fig. 11. The proposed cluster formation algorithm ensures the extended network lifetime with the increased node density.

- *Network lifetime*: it is the most essential parameter in WSN as most of the time, WSNs are deployed in inaccessible terrain. Network lifetime conveys up to what time the network sustains to perform the network operation. The number of alive nodes can give a measure for the sustainability of a network. After extensive simulations, we found that 4% of nodes remain alive in LEACH, 5% of nodes remain alive in *K*-means, 9% of nodes remain alive in T2FL clustering, but 14% of nodes remain alive in proposed GA-clustering. Fig. 12 presents the experimental results.

6 Conclusion and future works

It has been proven through many studies that the hierarchical routing protocols based on clustering provide a scalable routing solution for larger WSN applications. In this study, we have designed a routing protocol that obeys the principle of clustering utilising the concept of the GA. GA is a bio-inspired algorithm which provides a near-optimal solution when the search space is huge. The step by step operations of the GA is incorporated in WSN clustering and simulations have been carried out through a Java-based simulator. The proposed GA-clustering algorithm provides a promising result over LEACH, *K*-means and T2FL clustering and preserves a longer network lifetime. It is expected that the simulation results could provide a quick response to the ever-growing challenges in real-world scenarios. Our future research could be focused on multiple crossover points to find an optimised path in view of solving multipath routing problems in WSN.

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