IJARCCE

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 5, Issue 10, October 2016

Expanding the Existing Time Span of Wireless Sensor Network by Incorporating Differential Evolution Algorithm in Clustering

Sonia Battan[1], Lakshit Bakshi[2]

Student, ECE, M.I.E.T. Kurukshetra University[1]

Assistant Professor, M.I.E.T. Kurukshetra University[2]

Abstract: Wireless sensor networks gains attention of everyone as they have wide range of applications. Networks are divided into clusters which contain nodes. Energy optimization of these nodes and increasing their life time is the main issue to be considered. Cluster Heads are selected using various algorithms such as Leach, Genetic, Differential Evolution and many more. This research paper represents use of Differential Evolution Algorithm for selecting cluster head. The results show that the lifetime of network is improved by using this algorithm as compared to Genetic Algorithm.

Keywords: Differential Evolution (DE), Genetic Algorithm, Cluster Head, First End Node, Half End Node.

1. INTRODUCTION

Wireless sensor networks are composed of hundreds and even thousands of sensor nodes i.e. a set of self-directed sensors which are embedded in the environment wirelessly at a distance from each other in a connected way and their task is to discover events, to collect data and environmental information and to transfer them to a monitoring center. In fact, sensors have inbuilt processors and communication facilities. They have different ways to measure some physical quantities such as temperature, light, humidity, sound, etc. The applications of sensor networks are increasing day by day, and soon they are going to play a wider role in everyday life of human being. Nowadays, wireless sensor networks are one of the most debated topics of research in computer science, communications, industry, and many non-military fields. Some of these huge applications include monitoring and controlling industrial processes, monitoring health condition of systems, environment monitoring of firms, centers, and houses, health care, smart homes, traffic control, and so on [1-3,6,7,10].

In Wireless Sensor networks, Sensor nodes work with severe limited resources like battery power, bandwidth, memory and etc. Lifetime of wireless sensor networks depends upon battery power of nodes as every operation of node consumes energy; hence node goes out of energy. Harsh/remote application area makes it impossible to recharge or replace the battery of nodes. So, efficient energy consumption of nodes is the prime design issue for wireless sensor networks from the circuitry of sensor nodes to application level to network protocols. Clustering algorithms [4, 5] are considered energy efficient approach for wireless sensor networks. Clustering divides the sensor nodes in independent clusters which select their cluster heads and send data to it and later on after receiving date cluster head compile all data send it to base station.

Clustering algorithm proposed in this paper selects and optimize number of cluster heads by applying Differential Evolution algorithm. The results show that the lifetime of network is improved by using this algorithm as compared to Genetic Algorithm

2. REVIEW OF LITERATURE

In recent years, the interest on clustered WSN has generated a significant body of Research works. A CH (Cluster Head) may be elected by the sensors in a cluster or pre-assigned by the network designer. A CH may also be just one of the sensors or a node that is richer in resources. Also the cluster membership of a node may be fixed or variable.

This paper is based on the shortcomings of Genetic Algorithm (GA) and to improve all those shortcomings. First of all we have to understand GA which is as follows: Genetic algorithm (GA) [8, 9] is a randomized search and optimization technique and is widely used for solving optimization problems that have large number of possible solutions. GA is based on survival of fittest theory. GA starts with a set of possible solutions called initial population which is generated randomly. Each individual solution is called chromosome. Length of each chromosome must be same. A fitness function calculates fitness value of each chromosome. Chromosome with high fitness value is closer to optimal solution. Two parent chromosomes are selected for crossover to produce two offspring. Mutation is applied to randomly selected

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chromosome to obtain a better solution. Crossover and mutation generate next population. Few best fitness value chromosome of previous population are also selected in new generated population to ensure that the new generation is at least as fit as the previous. This process is known as elitism. This entire process is repeated until some stopping criteria are not matched. Now in this paper we will discuss DE.

3. NETWORK MODEL

For the proposed protocol following network assumptions are considered:
- All sensor nodes are homogenous.
- All nodes are stationary once deployed in the field and have location information.
- There is single base station located inside the field.
- The nodes are considered to die only when their energy is exhausted.

In wireless sensor networks, nodes are deployed randomly i.e. positions of nodes are not pre-engineered. Most of the energy of nodes is dissipated due to communication between two nodes and it depends on the distance between them. Both sending and receiving of data consumes energy. Energy dissipation model is shown in Fig. 1 and explained next.

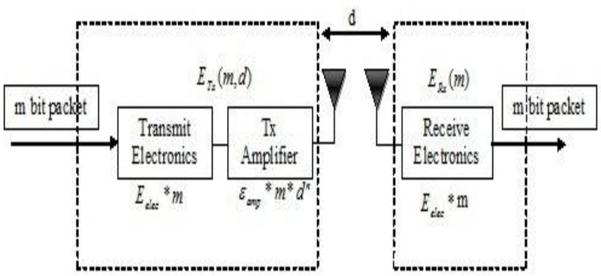

Fig. 1. Radio Energy Model

For sending m bit data over a distance d, the total energy consumed by a node is as follows:

$$E_{Tx}(m, d) = E_{Tx-elec}(m) + E_{Tx-amp}(m, d) \qquad (1)$$

$$E_{Tx}(m,d) = \begin{cases} m\times E_{elec}+(m\times E_{fs}\times d^2) & d < d_{crossover} \\ m\times E_{elec}+(m\times E_{amp}\times d^4) & d \geq d_{crossover} \end{cases} \qquad (2)$$

where $d_{crossover}$ is crossover distance, while the energy consumption for receiving that message is given by:

$$E_{Rx}(m) = m \times E_{elec} \qquad (3)$$

Considered network model for proposed scheme assumes energy required for running the transmitter and receiver electronic circuitry E_{elec} as 50nJ/bit and for acceptable SNR required energy for transmitter amplifier for free space propagation E_{fs} as 10pJ/bit/m2 and for two ray ground E_{amp} as 0.0013pJ/bit/m4. The crossover distance $d_{crossover}$ is considered 50m.

4. PROPOSED DIFFERENTIAL EVOLUTION ALGORITHM FOR CLUSTER HEAD SELECTION

4.1. Overview Differential Evolution Algorithms: Price and Storn developed DE to be a reliable and versatile function optimizer. The first written publication on DE appeared as a technical report in 1995 (Price and Storn 1995). Like nearly all EAs, DE is a population-based optimizer that attacks the starting point problem by sampling the objective function at multiple, randomly chosen initial points [11]. DE algorithm like genetic algorithm using similar operators; crossover, mutation and selection. DE has three advantages: finding the true global minimum regardless of the initial parameters values, fast convergence and using few control parameters.

The main difference in constructing better solutions is that genetic algorithm relies on crossover while DE relies on mutation operation. This main operation is based on the differences of randomly sampled pairs of solutions in the population. The algorithm uses mutation operation as a search mechanism and selection operation to direct the search toward the prospective regions in the search space. The DE algorithm also uses a non-uniform crossover that can take child vector parameters from one parent more often than it does from others. By using the components of the existing population members to construct trial vectors, the recombination (crossover) operator efficiently shuffles the information about successful combinations, enabling the search for a better solution space [13]. The DE algorithm is shown in figure2.

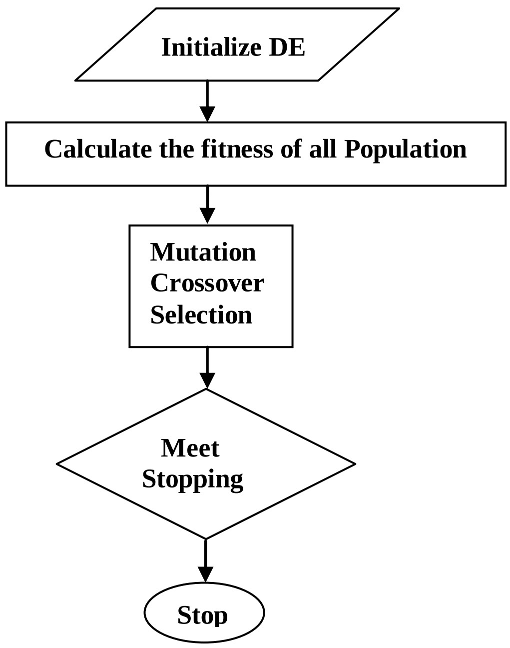

Fig. 2 The DE Algorithm

The basic DE algorithm can then be described as follows:

- Initialize all agents **x** with random positions in the search-space.

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- Until a termination criterion is met (e.g. number of iterations performed, or adequate fitness reached), repeat the following:
- For each agent $\mathbf{x}$ in the population do:
- Pick three agents $\mathbf{a}, \mathbf{b}$ and $\mathbf{c}$ from the population at random, they must be distinct from each other as well as from agent $\mathbf{x}$.
- Pick a random index $R \in \{1, \ldots, n\}$ (n being the dimensionality of the problem to be optimized).
- Compute the agent's potentially new position $\mathbf{y} = [y_1, \ldots, y_n]$ as follows:
- For each i, pick a uniformly distributed number $r_i \equiv U(0,1)$
- If $r_i < \mathrm{CR}$ or $i = R$ then set $y_i = a_i + F \times (b_i - c_i)$ otherwise set $y_i = x_i$.
- (In essence, the new position is outcome of binary crossover of agent $\mathbf{x}$ with intermediate agent $\mathbf{z} = \mathbf{a} + F \times (\mathbf{b} - \mathbf{c})$)
- If $f(\mathbf{y}) < f(\mathbf{x})$ then replace the agent in the population with the improved candidate solution, that is, replace $\mathbf{x}$ with $\mathbf{y}$ in the population.
- Pick the agent from the population that has the highest fitness or lowest cost and return it as the best found candidate solution.

Note that $F \in [0,2]$ is called the differential weight and $\mathrm{CR} \in [0,1]$ is called the crossover probability, both these parameters are selectable by the practitioner along with the population size $\mathrm{NP} \geq 4$.

4.2. Mutation: Once initialized, DE mutates and recombines the population to produce a population of Np trial vectors. In particular, differential mutation adds a scaled, randomly sampled, vector difference to a third vector. The scaled vector F is a positive real number that controls the rate at which population evolves. While there is no upper limit on F, effective values are seldom greater than 1.0.

4.3. Crossover: To complement the differential mutation search strategy, DE also employs uniform crossover. Sometimes referred to as discrete recombination, crossover builds trial vector out of parameter values that have been copied from two different vectors. In particular, DE crosses each vector with a mutant vector. The crossover probability Cr is a user-defined value that controls the fraction of parameter values that are copied from the mutant.

4.4 Selection: If the trial vector has an equal or lower objective function value than that of its target vector, it replaces the target vector in the next generation; otherwise, the target retains its place in the population for at least one more generation. Once the new population is installed, the process of mutation, recombination and selection is repeated until the optimum is located, or a pre-specified termination criterion is satisfied, e.g. the number of generation reaches a present maximum [12].

4.5 Encoding Scheme: In this, we have used binary coding i.e. 1 denotes cluster head and 0 denotes other nodes.

5. SIMULATION RESULTS AND ANALYSIS

Network parameters are listed in table 1 which are as follows:

PARAMETER	VALUE
Number of Nodes	50
Network Area	100x100m^2
Size of Population	N
Initial Energy	0.1J
Data Packet Size	4000bits
Probability	0.5

Network Lifetime: It can be defined as the working period of network [14] which defines network lifetime in by First Node Death (FND), Half Node Death (HND).

Table 2 Comparison of Network Lifetime of Genetic and Differential Evolution

Protocol	**FND**	**HND**
Genetic Algorithm	119	194
Differential Evolution Algorithm	203	212

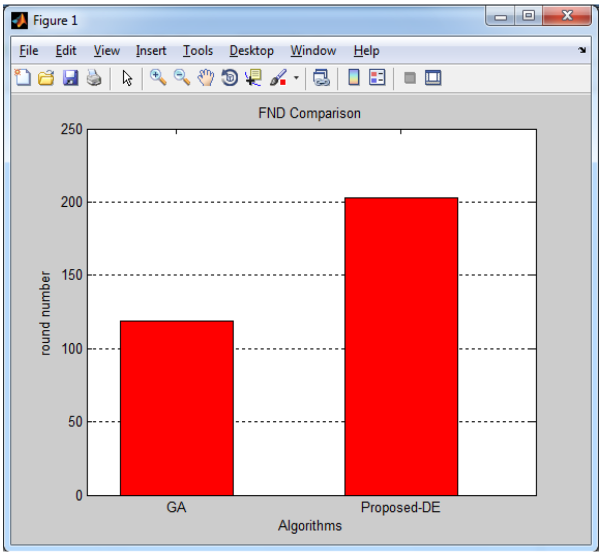

Fig.3 First Node Dead comparison between GA and DE

Figure 3 shows that the first node dead improves to a great extend after using DE as compared to GA.

Figure 4 shows that the energy consumption of the network has been improved after using DE.

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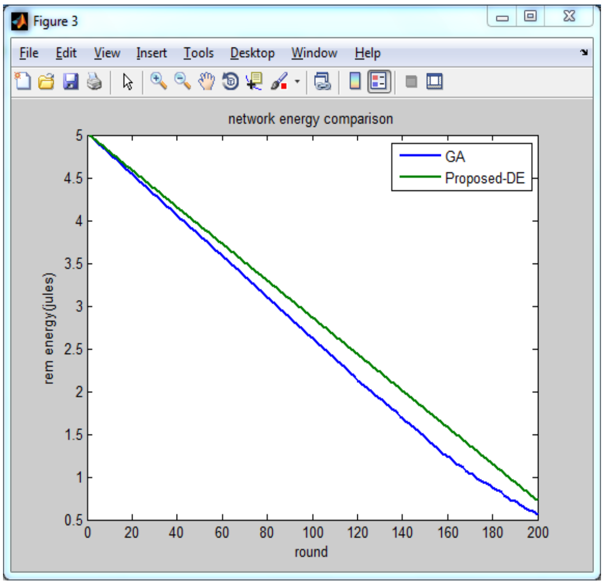

Fig.4 Energy Graph of GA and DE

6. CONCLUSION

The result of this paper shows that the FND (First End Node) improves after using DE as compared to GA. In DE, the first node which becomes dead works for more number of rounds and after FND, half node dead shows uniformity in network as whole network becomes dead. Instead of obtaining data from few parts as other nodes in a network are dead, it is better to improve the life-time for all the nodes to receive data from whole area uniformly.

7. FUTURE SCOPE

As in this paper we have only concentrated on one fitness parameter i.e. improving FND. Therefore in future other fitness parameters can be explored and variations can be done.

REFERENCES

[1] Bidyut Gupta, Shahram Rahimi, and Arun Kumar," A Novel Fault Tolerant Protocol for Information Propagation in Sensor Networks", IJCSNS International Journal of Computer Science and Network Security, VOL.6, No.7 B, July 2006.

[2] Farizah Yyunus, Nor-Syahidatul N. Ismail, Sharifah H. S. Ariffin, A. A. Shahidan, Norsheila Fisal, Sharifah K. Syed- Yusof, "Proposed Transport Protocol for Reliable Data Transfer in Wireless Sensor Network (WSN)", IEEE, ISBN: 978-1-4577-0003-3, 2011.

[3] Jinran Chen, Shubha Kher, and Arun Somani"Distributed Fault Detection of Wireless Sensor Networks", Dependable Computing and Networking Lab Iowa State UniversityAmes, Iowa 50010.

[4] Abbasi, A.A., Younis, M.. A survey on clustering algorithms for wireless sensor networks. Comput Commun 2007; 30(14-15):2826–2841.

[5] Tyagi, S., Kumar, N.. Review: A systematic review on clustering and routing techniques based upon leach protocol for wireless sensor networks. J Netw Comput Appl 2013;36(2):623–645.

[6] Mehrjoo, S., Aghaee, H., Karimi, H., "A Novel Hybrid GA-ABC based Energy Efficient Clustering in Wireless Sensor Network", Canadian Journal on Multimedia and Wireless Networks, Vol. 2, No. 2, April 2011, PP. 41-45.

[7] Nagi, E., Zhou, Y., R. Lyu, M., Liu, J., "A delay-aware realiable event reporting framework for wireless sensor-actuator networks", Journal: Elsevier, Science Direct, doi:10.1016/J.adhoc.2010.01004, 2010.

[8] Goldberg, D.E. Genetic Algorithms in Search and Machine Learning. Pearson Education; 2006.

[9] Gen, M., Cheng, R. Genetic Algorithms and Engineering Optimization (Engineering Design and Automation). Wiley-Interscience; 1999.

[10] Wu Guowei, Lin Chi, Yao Lin, Liu Bing, "A cluster based WSN Fault Tolerant Protocol", Journal of Electronics (CHINA), Vol. 27, No. 1, DOI: 10.1007/s11767-008-0126-4, January 2010.

[11] Juang C. and Liou Y., "On the hybrid of genetic algorithm and particle swarm optimization for evolving recurrent neural network," Proc. IEEE International Joint Conference on Neural Networks, pp 2285-3389, 2004.

[12] Juang C., "A hybrid of genetic algorithm and particle swarm optimization for recurrent network design," IEEE Transactions on Systems, Man and Cybernetics, Part B, 34:997-1006, 2004.

[13] Firpi H. and Goodman E., "Designing templates for cellular neural networks using particle swarm optimization," Proc. In Applied Imagery Pattern Recognition Workshop, 33rd, pp 119-123, 2004.

[14] Haase, M., Timmermann, D.. energy adaptive clustering hierarchy with deterministic cluster head selection. In: In IEEE conference on Mobile and Wireless Communications Networks (MWCN) (2002. 2002, p. 368-372.)