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Energy-Aware Data Aggregation in Wireless Sensor Networks Using Particle Swarm Optimization Algorithm

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Abstract

Today many researchers are paying attention to wireless sensor networks due to their vast use in different sciences all over the world. The recollection of energy resources is almost impossible because each node usually acts in natural environments. The awareness of this problem and the fact that each node loses parts of its energy in routing and transmission of data packets makes the use of data aggregation technique so important. Data aggregation algorithms mainly aim to increase the networks lifetime due to reduction of packets transmitted to other nodes. These algorithms are compared with respect to lifetime, Latency and data accuracy. This study presents an effective approach to reducing energy consumption in wireless sensor networks through clustering to increase general lifetime of the network. Our proposed approach uses particle swarm optimization algorithm. The fitness function is computed with respect to initial energy, centralization, average distance and the remaining energy of nodes. The evaluation of the proposed approach shows better performance comparing to other methods.

Keywords

Wireless Sensor Networks, Data Aggregation, Network Lifetime, Particle Swarm Optimization

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1. Introduction

Wireless Sensor Networks are suitable for areas which users cannot participate. First types of these networks were designed for military applications. By these networks, the army forces could communicate with each other without raising any special equipment [1, 7]. Saving energy is the most important challenge in wireless networks. Increasing network lifetime has always been attended due to limited energy in wireless sensor networks. Researchers seek to find different methods to increase the lifetime of these networks and thus, to reduce the energy consumption. One reason for this reduction is the exhaustion of resources which terminate the life of the network because they cannot be replenished.

Clustering is a known technique in reduction of energy consumption. Clustering prevents exchanging duplicate messages between sensor nodes and is done for different purposes. Data aggregation is one of these most important objectives. Gathering and aggregating data at the cluster head require a new technique to lower the number of packets transmitted to the sink because the Information transferred from the neighbouring nodes is repeated. This could be done using data aggregation technique. Nevertheless, cluster heads selecting methods play an important role in reducing energy consumption. Bio-inspired algorithms are alternatives to analytical techniques. Particle swarm optimization (pso) is a bio-inspired algorithm. We propose a technique for increasing the lifetime of sensor networks by combining data aggregation and clustering methods which uses pso to operate efficiently. The approach was presented based on energy-aware clustering algorithms using pso to select cluster

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heads with more remained energy compared to other nodes. Thus it aimed to increase the network lifetime using pso algorithm. We experimented our proposed approach and the results verified the efficiency of the approach in comparison with some others.

The organization of the paper is as follows. The related works are reviewed in section 2. Then in section 3 we study the noticeable points of pso algorithm and its applications. The proposed method is discussed in section 4. Section 5 is about performance evaluations of our proposed method. Finally, the paper is concluded in section 6.

Related literature

This paper visualizes the problems that affect the data aggregation techniques and also argues the function of data aggregation in wireless sensor networks by means of swarm optimization algorithm [2] on the basis of elephant cognitive behaviour which is called elephant swarm optimization. To solve the optimization problems, the algorithms of bio-inspired optimization mime the nature. We are interested in algorithms which are inspired by the nature principles. Thus to evaluate the elephant swarm optimization on the basis of respects, we compared the results with the leach protocol in order to find the better performances than leach protocol.

Esnaashari and Meybodi introduced a technique of data aggregation. In wireless sensor network every node is equipped with a learning automaton. In order to transmit its packets towards the base station, every node learns the path and also has some actions; each of these actions are correspond to one of its neighbour. Learning automaton helps the node finding the next best hop to perform data aggregation. The learning system characteristics are the ability to improve its efficiency with respect to time. The aim of learning system is functional optimization and it is not well known [5, 11].

In order to evaluate the proposed technique performance, we compared the results to other three techniques. The proposed technique performs better than all other techniques. There are two progresses in the proposed technique. In the first progressed, unlike the proposed technique, the data aggregation between the node and its two next nodes is considered to choose a neighbour. In the second progressed, a node selects a neighbour containing more residual energy when it can’t find a neighbour for aggregating data. In experimental, we compared the proposed technique to the first and second progresses in terms of the average consumption of energy and the number of received packets. The number of received packets and the average energy consumption in both first and second progresses was less. So, the speed of data aggregation can be higher [5].

In work energy consumption and network lifetime are correlated. The challenge of energy consumption affects the network lifetime. Clustering is a solution to this problem. Binding cluster head and Identifying nodes subset are the aim of clustering. The task of cluster head is gathering data in its cluster and sending them to the sink. Clustering results in data aggregation. Reducing energy consumption and increasing network lifetime are the quality parameters in wireless sensor networks. Reducing energy consumption is an important parameter in increasing the network lifetime. The vast use of these networks requires the quality parameters. Thus quality parameters of these networks should be supported [4].

The Particle Swarm Optimization Algorithm

The importance of increasing use of bio-inspired algorithms is not hidden to anyone. The reason for this claim is the existence of a reliable source in comprehensive and thorough support of it which is called nature. The particle swarm optimization algorithm comes from the migration of a group of birds looking for food. This algorithm is a part of group intelligence algorithms. The agents used in these algorithms are underlying elements in the nature structure which prove their cohesion group in computing environment. Group behaviour of people who participate with each other to achieve certain goals is a simple type of this algorithm. These algorithms have been useful in vast and varied applications until now, and also paved the way for new applications in the future and always attracted the researchers’ mind in the face of complex computational applications. Some agents such as ants, birds and even drops of water are patterned in group intelligence algorithms. These algorithms were the replacement of analytical methods, but despite the available generalities about them, there may be supplements for them in the future which will not replace them certainly so that by providing optimal solutions they will be remembered as their increasing functions.

At first some particles are formed accidentally. Each particle in the particle swarm optimization algorithm is the same as a bird in group bird’s migration. The particles, as the birds, move in space and look for the best local and global location. Each particle has a certain quantity that will be computed by fitness function. The fitness of the particle is higher, if it is closer to the target, such as the birds moving towards the food. When the best local and global location is found, the speed and the location of particles are updated by formula (1) and (2) [3].

1) $Vj(k+1)=Vj(k)+C_1*r_1(k)*(Lbestj-Xj)+C_2*r_2(k)*(Gbest-Xj)$

2) $Xj(k+1)=Xj(k)+Vj(k+1)$

The Code of the PSO algorithm in MATLAB is as follows.

```
for i=1: Particles Count
  particles(i).x=random(i,1);
 end
 for i=1: maxit
   for j=1: Particles_Count
     fit = Fitness(Particles(j). Energy(Particles(j).X,1),
     Sent Packets);
       if (fit > Particles(j). lBest)
         Particles(j). lBest = fit;
       end
       if (fit > gBest)
         gBest = fit;
       end
     Particles(j). velocity = Particles(j). velocity + (c1 *
     (rand (1,1)) *) Particles(j).lBest - Particles(j).X)) +...
   (c2 * (rand (1,1)) * (gBest - Particles(j).X));
   Particles(j).X = abs(mod(floor(Particles(j).X +
   Particles(j).velocity), Particles Count)+1);
```

Data aggregation is one of the wireless sensor networks problems. The request for optimizing algorithms is that speed of convergence and high quality of solutions are strengths of it. Particle Swarm Optimization is an algorithm used to solve wireless sensor networks issues. It is suitable for WSNs issues such as data aggregation. Although this knowledge is a new knowledge in bio inspired swarm optimization field, now it has developing applications.

The Application of Particle Swarm Optimization

Learning Automata

The learning automata have two types: constant automata and variable automata. In the former, the actions probability is constant and in the latter the repetition of action probability is updated. If automata with n-repetition choose an action and receives an optimal response from the environment, the action probability will increase and the other actions probability will decrease and vice versa.

$\{\alpha, \beta, p, T\}$ defines the variable automata. The action set is $\alpha = \{\alpha_1, \alpha_2, \alpha_r\}$, the input set is $\beta = \{\beta_1, \beta_2, \beta_r\}$, the action probability set is $p = \{p_1, p_2, p_r\}$ and the learning algorithm is $p(n+1) = T[a(n), b(n), p(n)]$. The automata randomly choose one action and performs it on a random environment. After evaluating the action and response, automata update its action probability set on the basis of formula (2) for suitable responses and formula (2) for unsuitable responses. a and b are reward and penalty parameters [5].

$$Pi(n+1) = Pi(n) + a(1-Pi(n))$$

$$Pj(n+1) = Pj(n) - aPj(n) \ \forall jj\neq i$$

$$Pi(n+1) = (1 - b)\, Pi(n)$$

$$Pj(n+1) = \frac{b}{r-1} + (1 - b)Pj(n) \ \forall jj\neq i$$

Learning automata is a way for optimizing the quality parameters such as reducing energy consumption and extending the lifetime of wireless sensor networks. These machines have a significant potential to solve the basic problems of sensor networks and are suitable for distributed environments.

2. Method

The optimization of energy consumption is an important criteria used to determine the network lifetime. Nodes clustering are a known technique to achieve the optimized direction. By clustering the data are placed in the cluster head and the repeated ones are omitted. Data aggregation is one of the most important goals in clustering and a great method in preventing sending duplicate data in the network. Thus, the overall energy consumption reduces as fewer nodes are placed in the informative packets direction.

The proposed competence function is computed with respect to initial energy, centralization, average distance and the remaining energy of nodes.

$$\text{Fitness function} = (1/\text{Round} * \text{Energy} / \text{Initial Energy}) + \text{Centrality} / \text{Distance} \quad (1)$$

Each parameter of the proposed competence function is calculated in following formulas.

The selection of suitable cluster heads is the main part of every clustering technique. By this, the selected suitable cluster heads affect the clustering technique performance at the end of each round. Internal and between cluster interactions are the most important indices for each cluster head.

Distance is calculated as follows:

$$Intra(c) = \sum_{i=1}^{C} \sum_{j=1}^{N} (Xj - Xi) \quad (2)$$

C the number of clusters, N the number of nodes, Xj the cluster head and Xi the distance of the nodes from its cluster head.

Centrality is computed using the following formula:

$$\text{Centrality} = \frac{\textit{The nodes number of neighbor}}{\textit{The total number of nodes}} \quad (3)$$

When the centrality increases, the cluster integration will increase and a better clustering will take place. The number of cluster head nodes will be decreased as well. This decreasing indicates decreased network energy consumption [13].

The Computation the remaining energy of nodes in Sending and Receiving data

$$\text{Energy}_{Send}(t) = \text{Energy}(t) - \text{election} * k + \text{amp} * k * \text{distance}^2 \quad (4)$$

$$\text{Energy}_{Receive}(t) = \text{Energy}(t) - \text{election} * k \quad (5)$$

The initial energy is also a fixed amount for all nodes in the network that is considered to be 1j.

Each node sends a message to the access point that performs clustering [9].

The approach was presented based on energy-aware clustering to select cluster heads with more remained energy compared to other nodes. The implementation of this technique is done by an access point. New cluster heads are selected in each round. Fitness function will be computed for all nodes to determine the accepted cluster heads. The access point computes the nodes average energy. Those nodes having greater energy than the average will be selected as the cluster head in each round. Finally, the access point performs the particle swarm optimization algorithm to determine the k-number of the best cluster heads.

The access point forwards this conclusion to all existing nodes in the network after selecting the candidate cluster heads. The selected cluster head makes a time table for each of its member to prevent the incidence of transmitted messages. The cluster heads integrate all data and transmit them to the access point after transmitting all nodes data.

3. Result

In this section, we compare bio inspired computational techniques based clustering optimization algorithms such as particle swarm, genetic and ant colony. We also evaluate the function of data aggregation technique using the particle swarm optimization algorithm compared to other optimization algorithms based on energy consumption and network lifetime criteria with different experiments. The intended optimization algorithms have been tested in the same conditions in order to compare their performances based on mentioned criteria. In this comparison the same initial values in terms of data packets length, the amount of initial energy of nodes and the consumed energy in each sending and receiving data is given to each optimization algorithm.

Table 1. Initial values of parameters.

Parameter name	Initial value
Amp	0.0013 $P^{J/bit/m4}$
Election	0.005 $n^{j/bit}$
Initial Energy	1000 mj
Packet Size	400 bit
Initial Position Particles	Randomize
C_1 C_2	2
r_1 r_2	Random numbers in [0,1]

In order to compare the performance of optimization algorithms, the average energy consumption and network lifetime criteria have been considered. To evaluate these two criteria, two types of experiments have been done.

3.1. Experiment 1

The aim of this experiment is the superiority of energy consumption optimization level of particle swarm optimization algorithm compared to evaluated algorithms. Figure 1 shows the average of nodes energy consumption in algorithms. As it is seen, the average of nodes energy consumption in particle swarm optimization algorithm is less than it in other algorithms.

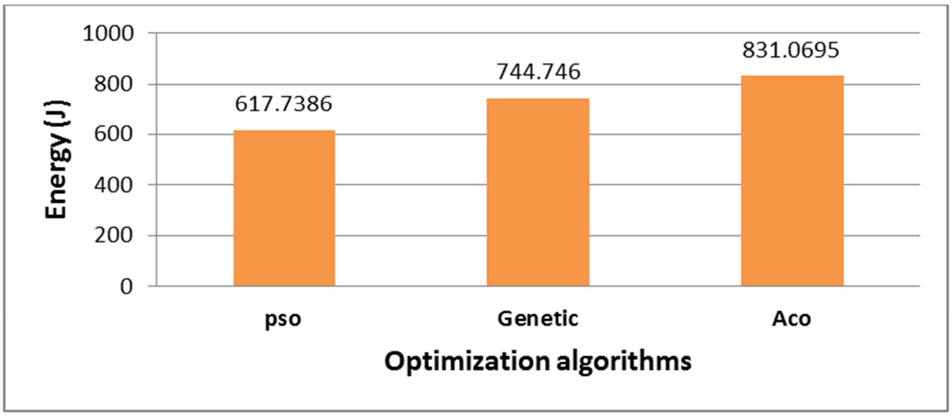

Figure 1. The average comparison of energy consumption.

Genetic algorithm in terms of average energy consumption of nodes has better performance than ant colony optimization algorithm. The reason for this success is the combination of successful generations in every round run that helps genetic algorithms to always provide the best answer.

3.2. Experiment 2

In this experiment, the network lifetime has been considered which is one of the main criteria of quality service in sensor networks. Figure 2 shows the results of this evaluation. As it is seen, the network lifetime is more than evaluated algorithms when the particle swarm optimization algorithm is used.

The experiments show the better results of data aggregation technique of the particle swarm optimization algorithm compared to genetic and ant colony optimization algorithms. Because particle swarm optimization algorithm always provides more confident answers with proper search in the problem space as well as the more velocity of particles that are closer to the optimal answer. Particles in next rounds go to any direction that local best and global best proposed. This can lead to appropriate choose of cluster head nodes. Because these nodes have been selected as cluster head in conditions that have been able to show the best performance in a broad search and in the final rounds of algorithm show their superiority compared to the other existing nodes just when the saved energy of nodes has decreased.

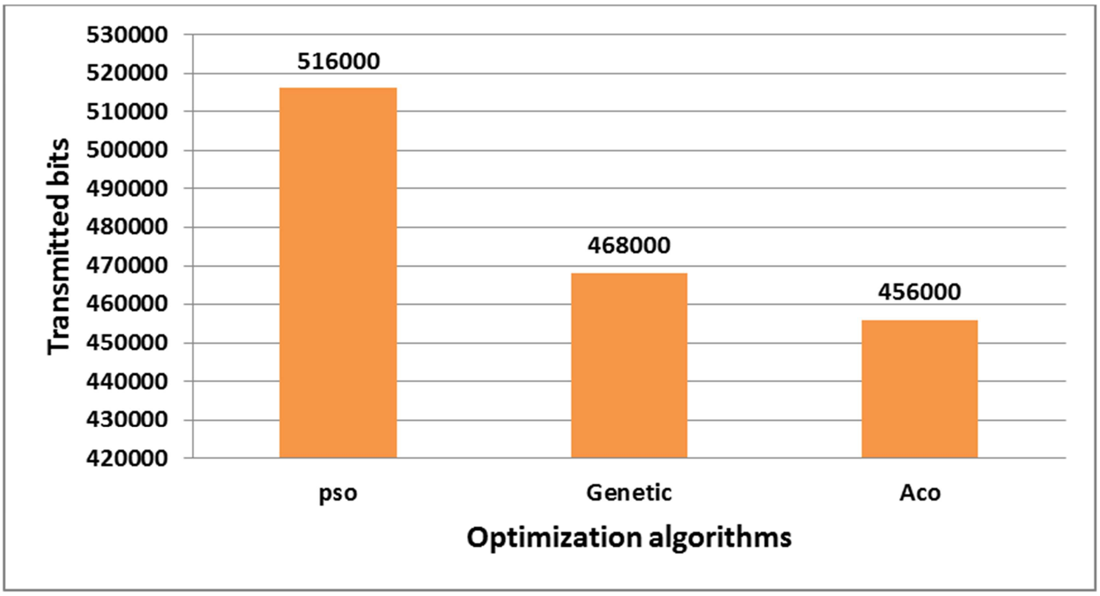

Figure 2. Network lifetime comparison based on the number of transmitted data bit.

4. Discussion

Considering the importance of energy in wireless sensor networks, usually due to lack of access to the nodes in specific environments in order to restore energy resources, the data aggregation method application seems to be essential. Data aggregation is one of the fundamental problems in wireless sensor networks. In this paper, a new approach is proposed to increase the lifetime of the network. The approach was presented based on energy-aware clustering algorithms using particle swarm optimization to select cluster heads with more remained energy compared to other nodes. Thus it aimed to increase network lifetime using pso algorithm. The fitness function of the proposed method is computed with respect to initial energy, centralization, average distance and the remaining energy of nodes. Eventually, computer simulations are performed to evaluate the function of proposed method. The findings are compared with two ant colony optimization and genetic algorithms. The final findings showed that the proposed method acts better than the other two methods with respect to the energy consumption and the network lifetime.

5. Conclusion

One of the most important advantages of particle swarm optimization algorithm is the production of high quality solutions due to its ability to escape from local best. In order to better search capability toward the creation of high quality solutions, a parameter called inertia weight (W) has been added coefficient to the algorithm in the speed parameter.

$$Vj(k+1)=WVj(k)+C1*rand(k)*(Lbestj-Xj)+C2*rand(k)*(Gbest-Xj)$$

The inertia weight determines the effect of particles speed in the previous step on current speed of particles. Thus, with large quantities of inertia weight, the general search capability of algorithm has improved and more space has been considered. Usually algorithm starts with the large quantity of inertia weight and such weight gradually decreases over time. This causes the concentration of search in a small space in the final steps and creation of local optimal problem that is the provided global best by algorithm in final steps is not the most optimal answer.

A proposed solution is the use of dynamic parameters at the right time by helping of fitness function so that by approaching to the final rounds the dynamic parameters change according to the fitness function. With this operation as we got to the convergence, we would expect that algorithm has an improvement to β times in next rounds. If not, dynamic parameters will search problem space with broader steps. This can cause the extensive search of the problem space and remove of the local optimal problem.

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