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Energy Optimization using Particle Swarm Optimization based on Clustering for Wireless Sensor Network

O. Deepa [1], Dr. J. Suguna [2]
Research Scholar [1], Research& Development Centre,
Bharathiar University, Coimbatore, TN, India.
Associate Professor [2], Department of Computer Science,
Vellalar College for Women, Erode, Tamil Nadu, India

ABSTRACT
Wireless Sensor Network (WSN) is a self-organizing network which formed with huge sensors which are located in an application specific environment to monitor the physical pheromone like temperature, fire, and pressure. Mostly sensors are equipped with battery power through which they can perform sufficient operations and communication among neighboring nodes. Researchers for WSNs face challenge that arises from limited energy. Maximizing the lifetime of the WSN, energy conservation measures are essential for improving the performance of WSNs. Particle Swarm Optimization (PSO) is used to form clustering and select cluster head with respect to minimizing the power consumption in WSN. This paper discusses about energy optimization using PSO based on clustering algorithms for WSN, which aims to extend network lifetime.
***Keywords* :–** Wireless Sensor Network, Particle Swarm Optimization, clustering, power consumption, fitness function

I. INTRODUCTION

In recent years, with the rapid development of wireless technology, sensors are receiving important attention, which leads to the emergence of directional sensor network. Wireless Sensor Network (WSN) is a self-organized network with huge, intelligent and small sensors. These sensors can perform the data transmission among themselves within their radio range and also they are organized in a way to sense, observe and recognize the physical entity of the real world [1]. WSNs integrate into the environment, machinery and human, coupled with the efficient delivery of sensed information, could deliver tremendous benefits to society. Some of the potential benefits are reinforced emergency response, preservation of natural resources, improved homeland security and enhanced manufacturing productivity. The significance of sensor networks have low energy consumption, sufficient intelligence for signal processing, low cost, self-organizing capability, data gathering and querying ability [2]. Wireless sensor is equipped with a radio transceiver, a microcontroller, an interfacing electronic circuit and an energy source usually a battery. The features of these sensors include tiny, low cost, low computation power, multifunctional and easy communication within short distances [3]. WSN consist of intelligent sensors, which has been arranged and installed based on the applications and a sink that is located very near to or within the radio range. The sink transmits the queries to the neighboring sensors which perform the sensing task and return the data to the sink as a response to the transmitted query [4]. In WSN nodes utilized is balanced amount of energy for communication and the required energy in terms of battery power to transmit the packet will differ among the transmissions with respect to the distance between the sender and receiver nodes; therefore multi-hop communication is recommended. Data transmission using hierarchical routing which increases the lifetime of the sensor network by grouping a number of nodes into clusters. Then a high residual energy node is selected for each cluster known as cluster head to collect the data from its members and transmit to the sink with a minimum cost of multi-hop transmission. Extended network lifetime, reliable data transfer, energy conservation in sensors and scalability are the main necessities for WSN applications [5]. Because of the several limitations in the sensors, WSN is having various issues such as coverage area, network lifetime and dynamic topology and data aggregation.

To enhance the network lifetime appropriately many routing protocols and cluster-based algorithms are used to fulfill the application requirements in WSN. From existing research methods, optimizing energy dissipation for communication becomes very critical. For maximizing lifetime of the WSN, part of an energy consumption of each sensor has an important role while communicating among other sensors. This paper focuses on energy conservation in each sensor by using PSO-based clustering algorithm. The cluster head is selected using PSO, based on the distance from the cluster member node to sink and the residual energy in that node.

The rest of this paper is organized as follows: optimization methods, PSO and its relative advantages are briefly outlined in Section 2.Cluster formation using PSO’s are discussed in Section 3. Energy-aware clustering optimization algorithms for WSN based on PSO are discussed in Section 4. Conclusion and scope for future work is given in Section 5.

II. PSO: A BRIEF OVERVIEW

A. Optimization Methods

For example to consider the following global optimization problem

$$\min f(x)$$
$$\text{subject to } x \epsilon X \qquad (1)$$

where x is a continuous variable vector with domain $X \subset R^n$ defined by the bound constraint $l_j \leq x_j \leq u_j, j = 1,2,..n$. The function $f(x): X \to R$ is a continuous real-valued function. Many real-world problems, such as engineering and related areas, can be reduced to formulation (1). This problem usually has many local optima, so it is difficult to find its global optimum. For solving such problem, researchers have presented many methods during the past years, which can be divided into two groups: deterministic and stochastic algorithms. Most deterministic algorithms usually effective for unique modal functions have one global optimum and need gradient information. However, stochastic algorithms do not require any properties of the objective function. Therefore, more attention has been paid to stochastic algorithms recently and many effective algorithms have been presented, including Simulated Annealing (SA), Genetic Algorithm (GA), Differential Evolution (DE), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Artificial Bee Colony (ABC), and Harmony Search (HS). Among these stochastic algorithms, PSO is a population based and intelligent method, which is inspired by the emergent motion of a flock of birds searching for food [6]. In PSO, a population of potential solutions is evolved through successive iterations. Since PSO algorithm has a number of desirable properties, including simplicity of implementation, scalability in dimension and good empirical performance, it has been applied to solve many real-world problems. Although PSO algorithm has been applied successfully in solving many difficult optimization problems, it also has difficulties in keeping balance between exploration and exploitation when solving complex multimodal problems.

B. Introduction to Particle Swarm Optimization

PSO is an optimization technique in which natural species social behaviors are considered for the purpose of computation, introduced by Kennedy and Eberhert in 1995 [7]. It is a swarm intelligence technique which isa population-based optimization scheme with the objective of optimizing a fitness function by updating the generations. The model of this algorithm is based on the social behavior of bird flocking. It is observed from the nature of birds which always travel in a group without colliding. The PSO technique uses several particles, each represents a solution and finds the best particle position with respect to a given fitness function. In PSO, each single solution is a particle (bird) in the search space. Each particle have fitness values that are evaluated by the fitness function to be optimized and stored record for all its coordinates which are related to obtaining the better solution by following the current best particles. The fitness value of the current optimum particle is called *pBest*. PSO optimizes the best population value that is obtained so far by any particle in the neighbors and its location is called *lBest*. When all the generated populations are considered as topological neighbors by a particular particle, then the best value is chosen among the generated population and that particular best value is the best solution and it is known as *gBest*. The PSO always try to change the velocity of every particle towards its *pBest* and *lBest*. The velocity is determined by random terminologies, which is having randomly generated numbers for velocity towards *pBest* and *lBest* localities. From the large deposit of generated solutions, the best one is selected to resolve the problem. The PSO algorithm always stores and maintains a record of results for three global variables such as target value or condition, *gBest* and stopping value. Every obtained particle of PSO contains: a data which can represent a global solution, value for velocity which will indicate the amount of data to be changed, *lBest* value [8].

In the past several years, PSO has been successfully applied in much research andcan be used across a wide range of applications, as well as for specific applications focused on a specific requirement. Advantages of PSO over these alternatives are ease of implementation on hardware or software, availability of guidelines for choosing its parameters, high-quality solutions because of its ability to escape from local optima, availability of variants for integer, real and binary domains and quick convergence.

C. PSO Algorithm

PSO is a popular multidimensional optimization technique [9], which explore an n-dimensional hyperspace in search of the global solution, where n represents the number of optimal parameters to be determined. A particle i occupies position X_{id} and velocity V_{id} in the d^{th} dimension of the hyperspace, $1 \leq i \leq s$ and $1 \leq d \leq n$ .Each particle is evaluated through an objective function $f(x_1, x_2, \ldots, x_n)$, where $f: \mathbb{R}_n \to \mathbb{R}$. The cost (fitness) of a particle close to the global solution is lower (higher) than that of a particle that is farther. PSO thrives to minimize (maximize) the cost (fitness) function. In the global-best version of PSO, the position where the particle i has its lowest cost is stored as $pbest_{id}$. Besides, $gbest_{id}$, the position of the best particle. In each iteration k, velocity V and position X are updated using (2) and (3). The update process is iteratively repeated until either an acceptable $gbest$ is achieved or a fixed number of iterations k_{max} is reached.

$$V_{id}(k+1) = wV_{id}(k) + \varphi_1 r_1(k)(pBest_{id} - X_{id}) + \varphi_2 r_2(k)(gBest_{id} - X_{id})$$

$$X_{id}(k+1) = X_{id}(k) + V_{id}(k+1) \qquad (3)$$

where φ_1 and φ_2 are constants and $r_1(k)$ and $r_2(k)$ are random numbers uniformly distributed in [0, 1]. The general pseudo code of PSO is shown in Algorithm I

```
PROCEDURE PSO( )
    BEGIN
    T=0;
    INITIALIZE PARTICLES P(T);
    EVALUATE PARTICLES P(T);
        WHILE (TERMINATION CONDITIONS ARE UNSATISFIED)
    BEGIN
        T=T+1;
        UPDATE WEIGHTS;
        SELECT PBEST FOR EACH PARTICLE;
        SELECT GBEST FROM P(T-1);
        CALCULATE PARTICLE VELOCITY P(T);
        UPDATE PARTICLE POSITION P(T);
        EVALUATE PARTICLES P(T);
        END
    END
```

Algorithm I – Procedure of PSO

III. CLUSTERING USING PSO

Clustering is an NP-hard optimization problem and is used for several effective energy protocols in WSN. The common operation of cluster-based protocol can be understood with the help of the following phases. In cluster formation phase, Cluster Head (CH) election takes place in a random manner. Once the CH election is performed, each CH broadcast an advertisement message toall the sensors, which arein the transmission range of a particular CH receives the message. The sensors or cluster nodes which then send a reply message with request message to join under the particular CH. In information processing phase, each sensor involves in sensing the attributes depending on the application. The sensed data from each node is transmitted to their respective CH. Once CHs receive the sensed data, it performs data aggregation and this process is repeated periodically. In data dissemination phase, each CH transmits the aggregated data to the sink based on the data dissemination interval.

PSO is a popular choice for WSN clustering because its optimization algorithm is simpler and the network efficiency is better. By using PSO for clustering, let us consider a sample space and deploy the particles or sensors in it. Let n be the number of particles considered in the sample space.

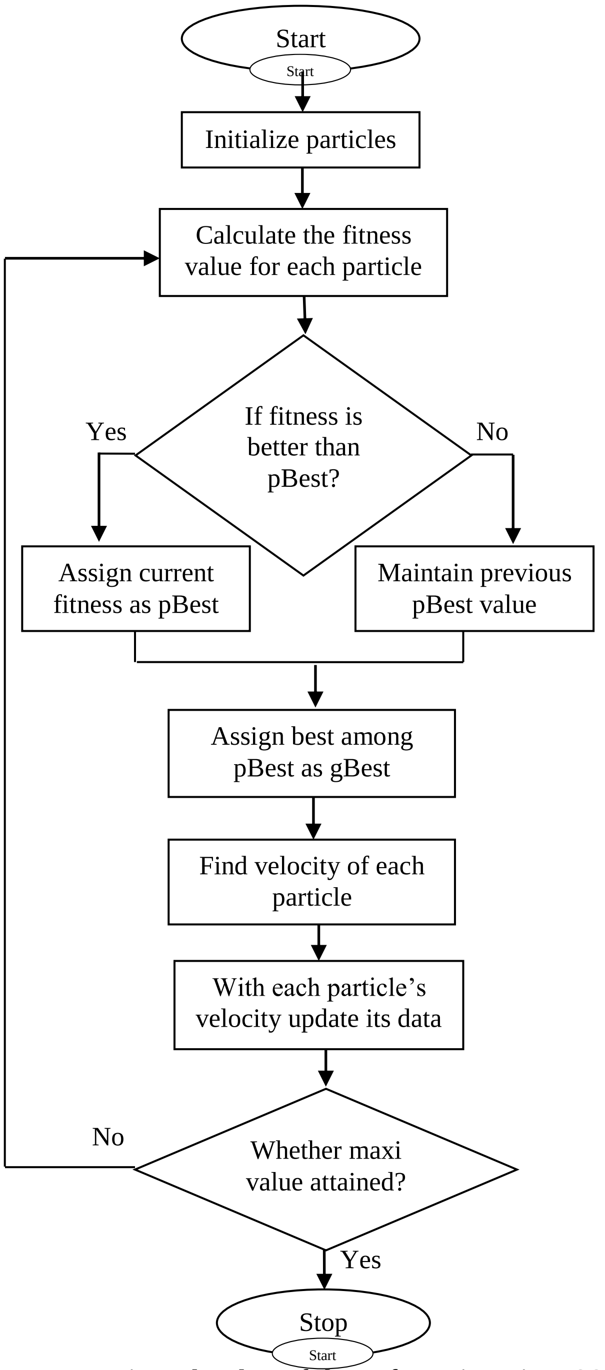

Fig.1. Flowchart of cluster formation using PSO

Particles are created by considering two parameters namely, position and velocity. Once the sensors are deployed in the sensor field, the sink broadcasts a request message to all the sensors in the network to collect the node's information. This in turn sends reply message to the sink which contains: position, velocity and energy of the sensor. These values are maintained and updated at the sink. Then the sink makes the sensors to perform clustering. Cluster formation is performed using PSO by allowing each sensor to find the nearest neighbor within its radio range. Likewise all the sensors in

WSN are allowed to form clustering, it become a part of any of the clustering. The same process is repeated until all the sensors become a member of any cluster in the network. The fitness value is calculated for choosing a cluster particle depends on the following factors namely, energy of the particle or sensor, energy of particles or sensors with in a radio range from a particular particle and distance of those particles within the radio range from a particular particle. Cluster particle is one in which more number of nodes are accessible in its radio range. The cluster particle can be generally referred as cluster head. Then, fitness function of each particle is calculated for each iteration [10]. Maximum fitness value in each iteration is called as *lBest* and maximum value among all iteration is called as *gBest*. If suppose, *gBest* value is obtained in the i[th] iteration, fitness values of all particles in that particular iteration are taken into account for cluster formation. Node with the maximum fitness value is taken as referenceand constructing the cluster by making the nodes in its radio range as its cluster members. The value of *gBest* is broadcasted to each cluster head so that, each head may aware of the *gBest* node. With reference to the node id the information is being transmitted. This process is illustrated in Fig. 1.

IV. ENERGY OPTIMIZATION USING PSO BASED ON CLUSTERING ALGORITHMS FOR WSN

The most important issue in this type of networks is energy constraints. In WSN, energy efficient routing protocols should be designed in an efficient manner in order to improve the network lifetime. The network lifetime is measured by the effective usage of the sensor in the network. Sensor in the sensing region is used to perform sensing, processing and communication. The overall network lifetime is based on the above said factors. The network lifetime can be improved by avoiding the sensor to transmit raw data. This can be achieved by aggregating the sensed data to eliminate the data redundancies, eliminating the control overhead messages and avoiding the long distance transmission. If a network is constructed by considering the above said factors, the overall network lifetime can be improved [11]. In this section, various energy optimization using PSO based on clustering algorithms for WSN was discussed, which aims to extend network lifetime.

D. PSO-Clustering

Guru et al. have proposed four variants of PSO, namely, PSO with time varying inertia weight (PSO-TVIW), PSO with time varying acceleration constants (PSO-TVAC), hierarchical PSO-TVAC (HPSO-TVAC) and PSO with supervisor student mode (PSO-SSM) for energy-aware clustering[12]. PSO assigns n_j nodes to each of the k cluster-heads, $j = 1,2, \ldots\ldots k$ such that the total energy loss due to physical distances E_{dd} is minimum. This is defined in (4), where D_j is the distance between cluster-head j and the sink

$$F = \sum_{j=1}^{k} \sum_{i=1}^{n_j} \left(d_{ij}^2 + \frac{D_j^2}{n_j}\right) \quad (4)$$

In PSO-TVIW, the inertia weight w is decreased linearly in each iteration. In PSO-TVAC, inertia weight is set constant and acceleration constants c_1 and c_2 are varied linearly in every iteration. In HPSOTVAC, the particle update is not influenced by the velocity in previous iteration; but, reinitialization of velocity is done when the velocity stagnates in the search space. Finally, in PSO-SSM,

$$X_{id}(k+1) = (1 - mc)X_{id}(k) + mcV_{id}(k+1) \quad (5)$$

where mc is a constant called momentum factor. Clustering is based on a simple idea that for a group of nodes that lie in a neighborhood, the node closest to the sink becomes the cluster head. A detailed comparative analysis of the algorithms for optimal clustering is presented. This scheme considers only the physical distances between nodes and their assigned cluster heads, but not the energy available to the nodes

E. PSO-C

Latiff et al. consider both residual energy and physical distances between the nodes and their cluster heads [13]. Each particle represents a combination of cluster heads. The fitness function for the centralized PSO (PSO-C) is defined as $\text{Cost} = \beta f_1 + (1-\beta)f_2$, where f_1 is the maximum average Euclidean distance of nodes to their associated cluster heads and f_2 is the ratio of total initial energy of all nodes to the total energy of the cluster-head candidates in current round. These are expressed as (5) and (6), respectively.

$$f_1 = \max_{k=1,2,\ldots K}\left\{\sum_{\forall n_i \in C_{p,k}} \frac{d(n_i, CH_{p,k})}{|C_{p,k}|}\right\} \quad (5)$$

$$f_2 = \frac{\sum_{i=1}^{N} E(n_i)}{\sum_{k=1}^{K} E(CH_{p,k})} \quad (6)$$

where N is the number of nodes out of which K will be elected as the cluster heads. |Cp,k| is the number of nodes that belong to cluster Ck in particle p. This ensures that only the nodes that have above-average energy resources are elected as the cluster heads, and that the average distance between the nodes and the cluster heads is minimum. They compare the results of the algorithm with those of LEACH and the LEACH-C algorithms [14]. The PSO-based clustering algorithms outperform GA, LEACH and LEACH-C in terms of the network lifetime and the throughput.

F. MST-PSO

Cao et al. have considered an interesting case in which a node and its cluster-head engage in a multi-hop communication [15]. The method computes a distance-based minimum spanning tree of the weighted graph of the WSN. The best route between a node and its cluster-head is searched from all the optimal trees on the criterion of energy consumption. Cluster heads are elected based on the energy available to the nodes and the Euclidean distance to its neighbor node in the optimal tree. The authors compare the performances of three mechanisms of cluster-head election based on energy, auto-rotation and probability. Routing and cluster-head rotation are treated as optimization problems and tackled through PSO. The results show that the PSO-based clustering methods ensure longer network life.

G. PSO-MV

PSO-MV protocol [16] is based on PSO method and the residual energy of cluster heads is higher than other nodes, the purpose of the approach is energy balance. In the PSO-MV method, to choose the best two nodes as cluster heads, namely Master Cluster Head (MCH) and other as Vice Cluster Head (VCH) and the tasks between the nodes can be categorized, where the MCH is responsible for data collecting and transmission and VCH is responsible for inter-cluster communications or intra –cluster communications to sink. PSO-MV clustering algorithm is based on routing of clusters included generation steps and transmission of data according to the set of nodes into clusters and threshold energy that shows to E_λ is chosen as follow

$$E_\lambda = \sum_{i=1}^{N} \frac{E_i}{N}$$

But the weakness of this algorithm is in selection the number of cluster heads optimum.

V. CONCLUSIONS

Scale and density of deployment, environmental uncertainties, and constraints in energy, memory, bandwidth, and computing resources pose serious challenges to the developers of WSNs. Issues of the node deployment, localization, energy-aware clustering and data aggregation are often formulated as optimization problems. Most analytical methods suffer from lack of convergence to the final solutions. PSO has been a popular technique used to solve optimization problems in WSNs due to its simplicity, high quality of solution, fast convergence and reduced computational burden. In this paper, an overview of optimization algorithms and a brief survey of recent PSO-based solutions to the WSN are presented. The network performance of the WSNs is enhanced by using PSObased on clustering algorithms in terms of increasing the network lifetime, throughput, residual energy and number of active nodes. From the current rate of growth of PSO-based applications, it is envisioned that PSO will continue as an important optimization technique in the field of WSNs.

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