Particle Swarm Optimization for Efficient Placement of Relay Nodes in Cluster-Based Wireless Sensor Networks

Suman Som[1], Marlom Bey[2], and Pratyay Kuila[3]

Department of Computer Science and Engineering
National Institute of Technology Sikkim, South Sikkim-737139, India
somsuman980@gmail.com[1], marlombey46@gmail.com[2], pratyay_kuila@yahoo.com[3]

Abstract. Sensor nodes (SN) have limited capabilities of coverage and connectivity. Relay nodes ensure backbone connectivity between SNs and base station (BS). Proper placement of relay nodes (RNs) has a major role in ensuring maximum coverage and connectivity in cluster-based wireless sensor networks (WSNs). The key issues that should be taken care of during RN placement are the minimum use of costly RNs, maximum coverage of the SNs, and maximum connectivity between the RNs and the BS. In this paper, particle swarm optimization (PSO) based RN placement is proposed for cluster-based WSNs. The proposed PSO technique considers multiple objectives such as the selection of minimum RNs, maximum coverage of SNs by the placed RNs, and maximum connectivity between RNs and BS. The simulation results show that the proposed PSO can achieve better placement of RNs and at the same time maintain the coverage and connectivity of the networks.

Keywords: WSN · Coverage · Connectivity · Multiple Objective · PSO.

1 Introduction

Wireless sensor networks (WSNs) have attracted many researchers for their potential applications in industries, agriculture, defense, etc [1]. In most of the applications, the sensor nodes (SNs) are randomly or manually deployed in the application area to sense or monitor the target regions or points. For a large application, it is not feasible for the energy-constrained SNs to transmit the data to the base station (BS). Note that the SNs are operated by a limited energy source or battery. Therefore, the relay nodes (RNs) are suggested to be deployed by many researchers to construct a backbone network between the SNs and BS [2, 3]. In such applications, the SNs join the RNs as cluster members, and the RNs act as the cluster head. The RNs collect the data from the SNs and send the aggregated data to the BS. The cluster-based WSNs are found to be more energy efficient than the conventional flat WSNs [1, 4–6].

While deploying the RNs, it is necessary to ensure that all the SNs are covered by a minimum of one RN so that all the SNs can join the cluster.

R. Murugan et al. (eds.), *Proceedings of the International Conference on Signal Processing and Computer Vision (SIPCOV 2023)*, Advances in Engineering Research 239,
https://doi.org/10.2991/978-94-6463-529-4_31

Moreover, connectivity between the RNs is also important as the RNs have to transmit the vital data to the BS. Deployment of a large and redundant number of RNs may solve the coverage and connectivity problem very easily. However, the RNs are comparably very expensive. Therefore, to design a cost-effective WSN application, it is equally important to use a minimum number of RNs. Design of coverage and connectivity aware WSNs is taken care of by many researchers [7–10]. However, the design of coverage and connectivity-aware cluster-based WSNs is yet to be explored.

In this paper, we have proposed particle swarm optimization (PSO) based RN deployment for cluster-based WSNs. The proposed algorithm considers the deployment of a minimum number of RNs in the application scenario and ensures coverage of all the SNs and connectivity between the deployed RNs. The problem is first mathematically formulated. Binary particles are used. The fitness function is designed by considering all the mentioned objectives.

Remaining of the article is organized as follows. The section 2 is composed of a literature review. An overview of PSO is given in the section 3. Section 4 represents the system model and problem formulation. The proposed work is represented in section 5. The simulation result is given in section 6. Finally, the research work is concluded with future directions in section 7.

2 Related Works

In [7], authors proposed the connectivity and coverage based on the scheduling problem, they have considered four different objectives. NSGA-II is employed for the problem. The problem is first formulated in linear programming (LP). The chromosome is efficiently designed and the validity of the chromosome is shown to be preserved after crossover and mutation operation.

Gupta et al [11] have proposed a genetic algorithm (GA) based scheme to find the minimum number of PP to place the SN from where SN can fulfill the k-coverage to the targets. Further in [3], the authors have proposed a based node deployment scheme for k-covered and m-connected WSNs. The efficient design of chromosomes is shown for both works. In [12] also, authors have proposed a GA-based SN deployment scheme to achieve coverage and connectivity. In [9], authors have proposed coverage and connectivity-aware energy-efficient scheduling of the deployed SNs by using the improved GA. Further in [13], the authors have shown an improvement by the use of a novel NSGA-II-based approach.

In [14], authors have proposed optimal cluster head (CH) selection and node placement in WSN. In this paper, they have tried to improve the problem of energy efficiency, secure node placement, and network lifetime. The main goal of this paper is to minimize the depth of the important cluster head (ICH) from the BS. In [15], authors have proposed GA-based cluster head (CH) selection for single and multiple data sinks in heterogeneous WSN where they have focused on the problem of network longevity. Further node deployment has been studied in [16–19].

3 An Overview of PSO

Particle swarm optimization (PSO) [20–22] is one of the popular nature-inspired population-based meta-heuristic optimization techniques. The technique is inspired by the social behaviour of birds, fish, etc. It can be seen from nature that while a group of birds is flying or a school of fish is moving from one location to another, collision between them does not happen. They generally maintain their velocity and position during the flight by observing their neighbours and eventually reaching their destination. The PSO is also based on a similar concept. Where each particle of this optimization technique provides the complete solution for the considered optimization problem.

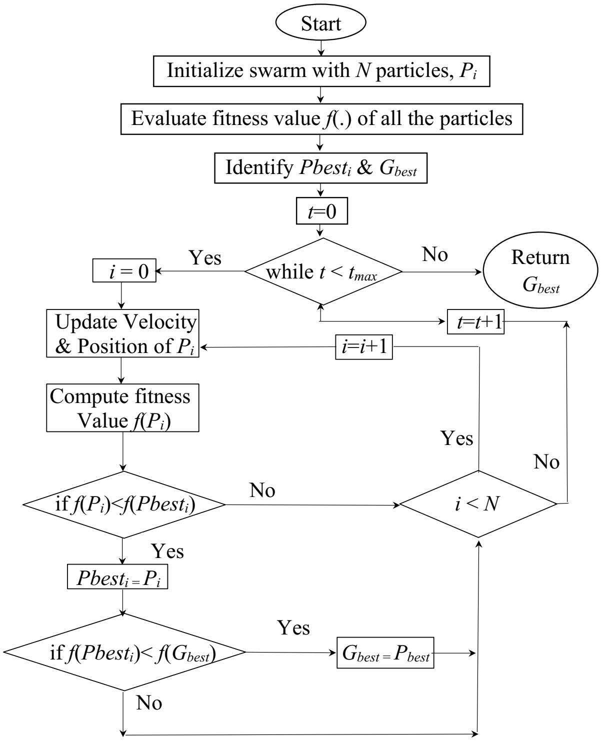


Fig. 1. Flow chart of PSO

Let us consider a swarm with N_P number of particles, i.e., the population size is N_P. A particle at t^{th} generation can be represented as, $\boldsymbol{P}_i^t = \{x_i^1, x_i^2, \ldots, x_i^D\}$, where D is the dimension of the particle and $1 \leq i \leq N_P$. x_i^d denotes the position component of the particle P_i in d^{th} dimension. Particle P_i^t has velocity, $\boldsymbol{V}_i^t = \{v_i^1, v_i^2, \ldots, v_i^D\}$. The quality of the solutions or particles is evaluated by the designed fitness function. In each iteration, the quality of the solution is improved by updating the velocity and position. The particle with the best fitness value in the population is denoted as global best, $\boldsymbol{Gbest}^t$. Each particle has a personal best which is the best ever experienced position. The personal best is denoted as, $\boldsymbol{Pbest}_i$. Each particle moves towards to new position by updating the velocity vector as follows.

$$\boldsymbol{V}_i^{t+1} = \omega \boldsymbol{V}_i^t + c_1 \times r_1.(\boldsymbol{Pbest}_i - \boldsymbol{P}_i^t) + c_2 \times r_2(\boldsymbol{Gbest}^t - \boldsymbol{P}_i^t) \tag{1}$$

After updating the velocity vector, the position vector is updated as follows.

$$\boldsymbol{P}_i^{t+1} = \boldsymbol{P}_i^t + \boldsymbol{V}_i^{t+1} \tag{2}$$

- ω represents the inertia weight factor which restricts the uncontrolled velocity of the particles.
- c_1 and c_2 are the cognition and social coefficients respectively.
- (r_1, r_2) are the random number between 0 and 1.

Each particle is evaluated by the fitness function to judge the quality of the solution. After updating the position, the current fitness value may be improved over the previous fitness value. Thereby, the personal and global best need to be updated. The personal best is updated as follows.

$$\boldsymbol{Pbest}_i = \begin{cases} \boldsymbol{P}_i^t, & \text{if Fitness}(\boldsymbol{P}_i^t) < \text{Fitness}(\boldsymbol{Pbest}_i) \\ \boldsymbol{Pbest}_i, & \text{Otherwise.} \end{cases} \tag{3}$$

If $\boldsymbol{Pbest}_i$ is updated then $\boldsymbol{Gbest}$ is updated as follows.

$$\boldsymbol{Gbest} = \begin{cases} \boldsymbol{P}_i^t, & \text{if Fitness}(\boldsymbol{P}_i^t) < \text{Fitness}(\boldsymbol{Gbest}) \\ \boldsymbol{Gbest}, & \text{Otherwise.} \end{cases} \tag{4}$$

All the particles in the population are updated accordingly. These processes will be continued till the termination condition. The flowchart of PSO is given in the Fig. 1.

4 System Model and Problem Formulation

4.1 System Model

Consider an application environment, where N number of SNs, $S = \{s_1, s_2, \ldots, s_N\}$ are deployed randomly or manually to monitor some critical targets in the industry. It is also assumed that there are M number of potential positions (PPs), $P = \{p_1, p_2, \ldots, p_M\}$ as shown in Fig. 2. Few relay nodes (RNs) are placed in the PPs to form clusters using the deployed SNs. Let us assume, Z number of RNs, $R = \{r_1, r_2, \ldots, r_Z\}$ are placed within the P number of PPs ($Z \leq P$). Here, the RNs act as the cluster head. The SNs choose the nearest RN as their respective CH. The RNs collect the data from their respective cluster members (SNs) and then aggregate the data. Finally, the aggregated data is transmitted to the nearby base station (BS) or edge server (ES). Here, the challenges are to place the RNs by ensuring coverage of all the SNs and connectivity amongst the RNs and the edge server. The following terminologies are used:

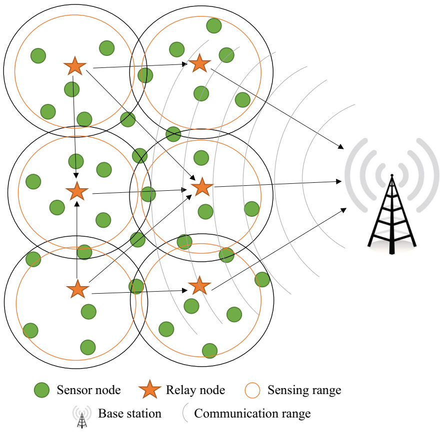


Fig. 2. A cluster-based WSN

- $S = \{s_1, s_2, \ldots, s_N\}$: the set of SNs.
- $P = \{p_1, p_2, \ldots, p_M\}$: the set of PPs.
- $R = \{r_1, r_2, \ldots, r_Z\}$: the set of RNs.
- R_{com}: the communication range of RNs.
- S_{com}: the communication range of SNs, $R_{com} > S_{com}$.
- $dis(r_i, r_j)$ denotes the euclidean distance between r_i and r_j.

4.2 Problem Formulation

To mathematically formulate the problem, the following Boolean variables are defined:

$$\delta_i = \begin{cases} 1, & \text{if } p_i \text{ is selected for } RN \text{ placement.} \\ 0, & \text{Otherwise.} \end{cases} \tag{5}$$

$$\omega_i = \begin{cases} 1, & \text{if } s_i \text{ has minimum one RN within the } S_{com} \text{ distance.} \\ 0, & \text{Otherwise.} \end{cases} \tag{6}$$

$$\phi_{ij} = \begin{cases} 1, & \text{if } dis(r_j, r_i) < R_{com} \text{ and } r_j \text{ is towards BS with respect to } r_i. \\ 0, & \text{Otherwise.} \end{cases} \tag{7}$$

$$\alpha_i = \begin{cases} 1, & \text{if } r_i \text{ is within } R_{com} \text{ distance of the BS/ES} \\ 0, & \text{else.} \end{cases} \tag{8}$$

The mathematical formulation of the problem can be expressed as follows:

$$\text{Minimize } Z = \sum_{i=1}^{P} \delta_i \tag{9}$$

Subject to

$$\omega_n = 1, \forall n, 1 \leq n \leq N \tag{10}$$

$$\sum_{j=1}^{Z} (\phi_{ij} \times \delta_j + a_i) \times \delta_i \geq 1, \forall i, 1 \leq i \leq Z \tag{11}$$

$$\delta_i \in \{0, 1\}, \forall i, 1 \leq i \leq M \tag{12}$$

$$\alpha_i \in \{0, 1\}, \forall i, 1 \leq i \leq Z \tag{13}$$

$$\phi_{ij} \in \{0, 1\}, i \neq j, \forall i, j, 1 \leq i \leq Z, 1 \leq j \leq Z \tag{14}$$

The constraint (10) ensures that each SN has a minimum of one RN within its communication range (S_{com}). Thereby, each SN can be a part of one cluster. The constraint (11) ensures that all the relay nodes are connected with the BS. The constraints (12)-(14) ensure ranges of the Boolean variables.

5 Proposed Work

In PSO, each particle represents a complete solution according to the problem.

5.1 Particle Representation and Initialization of Swarm

A particle represents a complete solution for the problem. Here, a binary particle with a length the same as the number of potential positions is considered. A swarm is a randomly generated N_P number of particles.

Illustration 1 *Let us consider a system with 8 potential positions, $P = \{p_1, p_2, \ldots, p_8\}$. Therefore, the dimension of the particle will be 8, i.e., the same as the number of potential positions. A randomly generated particle is shown in Fig. 3. The relay nodes are only placed to the corresponding PP with 1. Therefore, the relay nodes are placed on the PPs, p_1, p_3, p_6, and p_7.*

Potential Position (PP)	p_1	p_2	p_3	p_4	p_5	p_6	p_7	p_8
Selection of PPs	1	0	1	0	0	1	1	0

Fig. 3. Representation of particle

5.2 Fitness Function Derivation

Particles are evaluated by the derived fitness function. In this problem, the fitness function consists of the following objectives.

- **Objective 1** (Selection of minimum number of PPs): Our first objective is to select the minimum number of PPs to place the RNs. Therefore, our first objective can be evaluated from a particle as follows:

$$\text{Objective 1: Minimize } F_1 = \frac{1}{M}\sum_{i=1}^{M} x_i \tag{15}$$

- **Objective 2** (Maximization of coverage of SNs by the placed RNs): All the SNs should be covered by at least one RN. Let us assume $Cov(s_i)$ is the set of RNs that are within the communication range of s_i. Therefore, our second objective can be computed as:

$$\text{Objective 2: Maximize } F_2 = \sum_{\forall s_i \in S} Cov(s_i) \tag{16}$$

- **Objective 3** (Maximization of connectivity between the placed RNs): Let us assume $Con(r_i)$ be the set of r_j those are within the communication range of r_i and towards the BS with respect to r_i. Therefore, our second objective can be computed as:

$$\text{Objective 3: Maximize } F_3 = \sum_{\forall r_i \in R} Con(r_i) \tag{17}$$

The fitness function is:

$$\text{Maximize } Fitness = w_1 \times (1 - F_1) + w_2 \times F_2 + w_3 \times F_3 \tag{18}$$

where, $\sum w_i = 1$ and $0 \leq w_i \leq 1$, $\forall i, 1 \leq i \leq 3$.

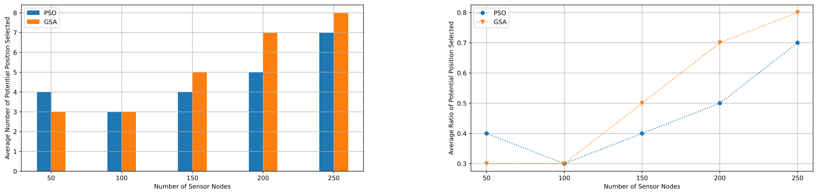
5.3 Updation process

Velocity and position of the particles are updated by the equations (1) and (2) respectively. Then the personal and global best particles are updated by the equation (3) and (4) respectively. The process will be continued till the termination condition. In the end, the global best particle, *Gbest* is selected as the final solution.

6 Simulation Result

For evaluation, two different scenarios are considered with different numbers of PPs. In the first scenario, 10 PPs are considered for 50 number of SNs. Similarly, in the second scenario, 10 PPs are considered for 100 number of SNs.

We have also executed the gravitational search algorithm (GSA) with the same fitness function and performance is compared with the proposed PSO. Fig. 4(a) shows the comparison with respect to the average number of selected PPs in scenario 1. Fig. 4(b) shows the comparison with respect to the ratio between the selected PPs and given PPs. Similarly, the simulation is also conducted for scenario 2. Here, only the placement of RNs is considered. Further routing can be done by using the existing algorithms as presented in [23, 24].



(a) (b)

Fig. 4. Comparison of (a) the number of PPs selected in scenario 1, and (b) the ratio between the selected PPs and given PPs in scenario 1

7 Conclusion

In this paper, we have proposed a PSO-based approach for the placement of RNs in cluster-based WSNs by considering coverage of the SNs by the placed RNs and connectivity between the placed RNs with the BS. The proposed algorithm tries to deploy a lesser number of RNs to form clusters and ensure connectivity. The fitness function is accordingly designed. The simulation is conducted and a comparison is done with GSA.

The energy efficiency of the relay nodes and sensor nodes is not considered. Further, load balancing of the RNs should also be considered. In the future, we will extend this work by considering the mentioned objectives too.

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