

Wireless Sensor Networks Optimal Node Placement by Soft-Computing

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Abstract— Wireless sensor networks (WSN) are now becoming an evolving technology and being vastly used in industries, engineering science, and military areas. To make this technology more commonly available; certain aspects of WSN need to be considered. This research paper shows how the PSO method is better than the genetic algorithm for verifying the proposed architecture of WSN. The major issues highlighted in this study are field coverage and network energy. Genetic algorithm is good at verifying the proposed optimized WSN architecture but the results stated in this paper show that the PSO method is a much better contender at verifying results.

Keywords: Particle swarm optimization, Genetic Algorithm, Wireless Sensor Networks, Node Placement and Network Configuration

I. INTRODUCTION

Nowadays, industries are able to create things which were not even imaginable in the last three decades and this is only because of modern science. Today's industries are becoming computerized and are using robots for production and manufacturing of goods. For implementing these technologies in industries, Wireless Sensor Networks play a vital role. WSN are useful in an environment where user accessibility is an imperative aspect. Different techniques and technologies make these sensors accessible and hence now WSN is not only useful in industrial areas but in other areas as well.

A. Wireless Sensor Networks (WSN)

A WSN consists of low power, cheap and multipurpose sensory devices. These devices include certain processing components like microprocessors and radio transceivers that are usually small in size. These components add data processing and communication capabilities into the sensor nodes along with their sensing capability. WSN have radio channels which make it possible to communicate over short distances and have different useful applications in different fields like civilian, industrial, environmental monitoring and military [1]. A WSN's characteristics and structure rely on their mechanical and electronic structure. Other factors include the limitations of communication and the nature of application [2].

B. Components OF WSN

There are four components of WSN i.e.:

- Controlling Unit: This component provides facility of controlling and processing of data.
- Sensors: They are useful for sensing signals and receiving or transmitting data to and from a particular environment.
- Power Supply: This unit provides energy for data communication and data sensing.
- Receiver/Transceiver: These components support communication among different nodes over a wireless medium.

C. Applications OF WSN

They are many applications of WSN and no one can ignore these benefits. WSN play a major role in different fields which include general engineering, environmental monitoring, and civil-engineering, military and health care. WSN is also used in sensing human interactions and social behaviour [3]. It provides a lot of benefits in the military field as well [4].

D. Limitations, Issues and Flaws OF WSN

The unique characteristics of WSN create lots of challenges in its design and deployment. These are as follows:

- Energy Consumption: Sensor nodes use energy power for their sensing functions and transmission of data. They have limited energy capacity. This creates a big challenge for node deployment in terms of their software and hardware placements. Also, it creates a challenge for their architecture and protocols designs. To enlarge the life time of sensor networks, energy consumption is a critical issue. In existing sensor networks, the energy consumed by nodes in data processing is usually less than data transferring [5].
- Network Connectivity: Network connectivity is another design issue of WSN. It actually depends on the protocol used for a particular application. Mostly, cluster based architecture is used for communication protocols that include different issues like no. of nodes in cluster, position of head

node, load handling capability of the sink nodes and ability of sensor nodes to reach these sink nodes [6].

- **Network Coverage:** Network converges is a major issue for the WSN design since the WSN has a limited range for communication. It is for this reason that placement of nodes and base station is the main area of research in WSN studies. The position of nodes or base stations should be done in a manner in which the whole specified area is covered.

E. Problem Statement

Developers of network protocols are facing challenges in the field of wireless sensor networks in terms of minimizing the energy consumption and maximizing network coverage [3]. Many researchers have optimized WSN parameters by using a genetic algorithm. However, there are other evolutionary algorithms like particle swarm optimization and tabu search. Tabu search is useful for improving the global minima which is a problem of GA. In a previous independent study, I have worked on the same issue using genetic algorithm and modified an already proposed algorithm by Bhondekar et al [6]. In this study we are trying to improve the results to avoid local minima using other nature inspired soft-computing suitable techniques, such as particle swarm optimization. Here, the objective is to improve the efficiency of optimization of node placement in wireless sensor networks. These algorithms help us to implement a self-organized wireless sensor network that can manage its position according to some design parameters that have optimal energy consumption and network coverage.

II. LITERATURE REVIEW

WSN has many applications in different areas but its problem of coverage and network energy consumption requires research. Many researchers have proposed solutions with different approaches like genetic algorithm, fuzzy logic, neural networks and etc. In my study, I have tried to improve results of genetic algorithm by using particle swarm optimization.

A. Particle Swarm Optimization

PSO is an evolutionary approach which models the social behaviour of fish schooling and bird flocks, developed by Kennedy and Eberhart [7]. It consists of a group of candidates called particles which move in hyperspace to find out the global optimum solution [8]. PSO is used in different fields like evolving artificial neural networks, system designs, multi-objective optimization, classification, biological system modelling, scheduling, pattern recognition, signal processing games, robotics application, simulation and identification and decision making [9].

1. *Description of PSO:* The difference in other evolutionary algorithms and PSO is that it does not use evolutionary operators to manipulate different objects instead, PSO uses velocity factor. Each individual in the PSO flies in search space with particular velocity which is dynamically updated by using its own flying experience and other neighbours' flying experience [10]. Each particle retains its coordinates in the search space which shows the best fitness it has achieved so far. This value is called 'pbest'. Another best value called global best 'gbest' is retained by using the global version of PSO is the overall best value of the search space. There is also a local version of PSO in which each particle doesn't only retain "pbest" but the "lbest" value as well which is obtained within the local neighborhood of particles [9].

I. *GBEST MODEL:* The GBEST version of PSO is the original PSO and its basic steps are given below;

- Initialize an array of candidates with arbitrary positions and velocities on d dimensions.
- Find fitness function cost value for each variable.
- Compare results with candidate's previous best value (*PBEST*):

If present value < *PBEST* then *PBEST* =
present value and
PbestPosition = current position

- Compare results with group's previous best (*GBEST*):

If present value < *GBEST* then
GBEST=candidate's array index,

- update velocity by the following formula:

$$Velocity[k + 1] = w * Velocity[k] + C1 * rand(x) * (pbestPosition[k] + C2 * rand(x) * (GBestPosition[k] - position[k])) \quad (1)$$

- Change position by following formula:

$$position[k + 1] = position[k] + velocity[k] \quad (2)$$

Go to step (b) and repeat until a condition is met [11].

Where 'W' is inertia weight and 'C1' is the self-experiential factor and is a constant between 0 and 2 that finds the "confidence" between the Gbest and Pbest. The larger 'C1' is the more particles will be placed around the global best. 'C2' is the swarm

experiential factor and is a constant between 0 and 2 that determines the point between the G_{best} and the P_{best} ; that is the standard deviation from both [12] [13]. Velocities of particles on each dimension are restricted to a maximum velocity V_{max} . It defines the value with which particles can move in a specified range of search space, without crossing any boundary. Large values of V_{max} are good for global search, while lower values of V_{MAX} are good for local search; whereas inertia weight is useful for both types of search as it can control both factors. So, the concept of developing the inertia weight is to eliminate the need of V_{max} [9].

2) *PSO versus GA*: WSN are now becoming one of the most popular technologies in the market today and mostly used in industrial and other fields. The main issue in WSN is to optimize its field coverage and network energy. PSO is the most appropriate optimization process for WSN, majorly because of its self-organizing capability. Alongside this, PSO has other advantages over GA as well which are given below:

- PSO and GA share some similarities like GA and PSO initialize particles with random positions and velocities. Each particle is evaluated by using some objective function and the population and search optimum result are updated using a random technique [15].
- Unlike GA, PSO does not use any evolutionary operators such as cross over and mutation [15].
- In GA, the population is updated by using some genetic algorithm while in PSO each particle updates its internal velocity by using the velocity they update themselves [15].
- PSO has memory while GA does not have memory which means that in PSO each particle retains all the best values which are achieved so far while in GA individual (chromosome) only retains their current values [11].
- In PSO the interaction among particles are different than in GA. In GA, the whole chromosomes share its information and the whole population moves toward one optimum solution while in PSO only the best particles share information to all other particles and they move towards the best particle. There is only one way of sharing information [15].
- PSO has the ability to control convergence by controlling inertia weight or maximum velocity [16].
- PSO is useful for optimization of multiple local optima by using its local version while GA sometimes fails to optimize the local optima [17].
- PSO is easy to implement while GA requires some complex computations. Unlike GA, PSO has few parameters to settle down and requires less computational resources of memory and speed. This results in faster convergence rates than GA. Due to

this feature; PSO is a useful algorithm for optimization of deployment in sensor networks [18].

B. Discussion and Analysis of Related Work

A lot of work has been done since the late 1980s in the field of WSN, where many optimized solutions have been proposed. Most of these solutions are based on optimization of the power consumption and field coverage issues. However, there is still a lot of room for improvement in this field. Here, I have discussed and analysed some of the most appropriate proposed solutions. The architecture and layout of IWSN are not the same as WSN so the method of node deployment of WSNs and Industrial WSNs are different. During the designing of IWSN layout, different factors are considered such as reliability, cost and energy balance. One method of optimal node placement in IWSN was developed by W. Ling using Adaptive Mutation Binary Particle Swarm Optimization (AMBPSO) [14]. In this study, the main objective was to design a layout of IWSN in such a manner that it has uniform communication load on different routes which would minimize the maintenance cost as well as provide data reliability. For maintenance, they used a cluster head node which has more communication load than regular sensor nodes. They designed a fitness function which solved this multi-objective optimization problem and considered all above defined factors. They restricted their design on some constraints of load and reliability. They also considered the equilibrium concept in communication load of the cluster head which balances energy consumption. They introduced the discrete binary version of PSO by modifying basic PSO which was basically designed for solving the continuous optimization problems. To solve the binary discrete problem, they just reversed the velocity updating formula. For large IWSNs, they introduced adaptive mutation BPSO called as AMPBPSO. They simulated their results by using MATLAB and compared results with GA and DBPSO. The results showed that AMPBPSO helps in finding a better schedule of placement and provides faster convergence [14].

In WSNs, there is one other method of reducing power consumption by arranging sensor nodes in a linear array. WSN sensor nodes have an Omni-directional antenna which transmits its information in all directions. By arranging it in a linear fashion it causes less power consumption as it will restrict radiation in other undesired directions. This is done by forming narrow beams for transmission of data. One method was introduced by N. N. A. Malik et. al[15]. The challenge for them was to arrange sensor nodes in a linear fashion as nodes are randomly distributed. They used PSO to optimize and localize those nodes which take part to form a linear array LSNA with a minimum side lobe level. They formed a sensor model and found the linear array factors by considering sensors in clusters. Each cluster has a centre node that manages and selects those nodes which take part to form an LSNA. By using array factors, they generated a fitness function which calculated the power consumption of WSN. By using PSO they arranged the sensor nodes in

a linear array and optimized the coordination of nodes with minimum SLL which reduced the over all power consumption. They performed two experiments one by using PSO-LSNA and the other using LSNA. Their results showed that the PSO-LSNA performs well for optimization of linear sensor nodes array for WSN [15].

For coverage, there was one research done by W. Ismail et. al [16]. They used PSO to locate the sensors in the region of interest and by using grid based strategy they calculated the coverage performance. In their research, they found the actual parameters which cause less field coverage and tried to minimize them. Basically, Grid points are used in two ways either to find out the sensors' position or to calculate coverage. PSO algorithm is executed on base station which decides the actual positions of nodes through which they move towards their final destination. Their main objective was to minimize coverage holes. They simulated their proposed approach by using MATLAB and tested different scenarios and found out the effect of number of sensor nodes and size of range of interest. Their simulation results showed that by using PSO, a better coverage can be achieved without affecting the number of sensor nodes and range of interest [16].

To design an efficient layout of WSN is also a challenging task; one approach was proposed by P. M. Pyari et. al [17]. In their research, they tried to provide an efficient layout of WSN with minimum energy consumption and good coverage by using multi-objective PSO. Each sensor node transmits its data to HECN (Higher Energy Consumption Node), which is responsible for collecting all data from nodes and sending it to DPU (Data Processing Unit). They considered two objectives in their research which were to maximize coverage and to maximize lifetime. They designed two fitness functions and used MOPSO to optimize the location of nodes in such a way that it provided good coverage with good life time. Their simulation results provided some pareto-optimal layouts from which the end user can chose the layout depending on the trade-offs between coverage and lifetime. They used a binary sensor coverage model and a stochastic sensor model in their experiment; their results showed that the binary sensor model gives better coverage. The only set-back of their research was that they ignored energy consumption due to sensor movements [17].

L. Zhimming et. al [18] performed node deployment in WSN by using improved particle swarm optimization. In PSO, there was a problem of premature convergence and they removed this problem by using some probabilistic detection and provided an improved form of PSO. They used a probabilistic approach to calculate coverage. All sensor nodes are groups in a cluster and each cluster has a CH with it that executes improved PSO which uses a fitness function of coverage and provides the desired destinations. They simulated their proposed approach and compared the results with a basic Virtual Force algorithm. Their simulation results showed that IPSO works well in sensor deployment with less energy consumption and enhances the network coverage ratio and network survival time [18].

Different approaches for node localization in sparse network were developed. One such approach was proposed by K. S. Low et. al [19] as they used a deploying agent who is a person who is equipped with some microcontrollers like pedometer and electronic compass. An electronic compass helps in finding the angle while a pedometer helps to find out the distance among nodes. They used a probability based algorithmic approach to find out the fitness function which used the information provided by the deployment agent and RSSI. This fitness function helped to find out the exact position of nodes where it provides good coverage. PSO is responsible for the evaluation of the fitness function value for each node and to update its velocity and position accordingly. They tested their approach by placing 30 nodes in the campus of Nanyang Technological University. Their results showed that there was a propagation error if only the pedometer information was used by the fitness function. By using additional information of RSSI, a better understanding of the estimation of the position of nodes was found. After this, they implemented their proposed PSO by using microcontrollers which were programmed with C language. Their results showed that by using PSO, the propagation error is reduced and they compared their results with other conventional approaches that showed high errors [19].

III. ANALYSIS OF PROPOSED SOLUTION

In my first IS, I have solved this issue by using a genetic algorithm which was a modification of an approach purposed by Bhondekar et al [6]. In this study, I'm using PSO to improve the results generated by the GA. In this study, I am using IEEE standard 802.15.4d which supports the distributed architecture. In this standard, the Wireless sensor supports 16 to 24 channels and a 2.7 GHZ frequency. I am using a different type of sensor called the FFD (Fully Functional Device) that can work like a regular node and a sink node. In my research, I am using 100 sensor nodes that are of three types (AP type nodes, SN type nodes and RN type nodes). AP is the access point which is only one in my proposed solution, while RN is the regular node but can work like a sink node as well as a regular sensor node. When RN starts working like a sink node then they are called SN (Sink Node) otherwise they are simple regular nodes.

Bhondekar et. al [6] solved this problem by using a multi- objective GA by optimizing different parameters. I have tried to optimize only two parameters due to some architectural change which are Field coverage and Network Energy. The main objective is to achieve good field coverage in minimum network energy consumption.

A. Application Specific Parameters

1) *Field coverage*: Each sensor node covers some area that is represented by the FC parameter. Since an AP node is treated as access point it is assumed to be one in my proposed solution. As RN can work like

both access point and regular sensor node called as SN, therefore its field coverage is equal to the access point. Regular sensor nodes can be inactive or active. Only active nodes participate in the calculation of field coverage.

$$F_c = \frac{(2 * AP + 2 * SN + RN) - inactive}{Total_nodes} \quad (3)$$

B. Energy Related Parameters

1) *Network Energy*: The AP type of node is treated as the access point and is assumed to be one in my proposed solution. As the RN type of node can work like both access point and regular sensor node, called as SN type of node. Therefore, its energy consumption is equal to the access point AP that is twice the energy power consumed by simple regular node. Network energy is calculated by the following equation;

$$NE = \frac{(RN + 2 * SN + 2 * AP)}{Total_Nodes} \quad (4)$$

C. Simulation Parameters and Assumptions

I have applied my simulation process using PSO under 200 generations to verify the outcomes in MATLAB. I have applied my proposed architecture considering the field of 10 x 10 units of area. In order to optimize the field coverage, I have used a total of 100 nodes which include one AP sensor node, forty SN sensor nodes and remaining are of RN type sensor nodes. Sensors which will not be in use in the simulation process will be considered as inactive nodes. As AP type of node is the access point, it is only one in my proposed solution, RN type of node can work like both Sink Node and simple regular node when they work like Sink Node they are called SN type of nodes. I also assumed that sensors used in this simulation process comply with the IEEE standard 802.15.4d. Therefore, these sensors can support up to 2.7 GHz frequency and maximum 26 channels. In this case, very few numbers of sensors can cover the required field.

1) *Field Coverage*: The following table shows the results of field coverage by using different values in the parameters;

TABLE 1
FIELD COVERAGE RESULTS

Particle Inertia (PI)	Social Interaction (SI)	Cognitive Interaction (CI)	No of Generations	Best	Mean
0.9	0.5	0.5	175	0.99005	0.992737
0.9	0.5	1	160	0.990003	1.00235
0.9	0.5	1.25	190	0.990032	1.5081
0.9	1	0.5	200	0.990007	0.992875
0.9	1	1	175	0.990062	1.0289
0.9	1	1.25	140	0.995502	1.67642
0.9	1.25	0.5	225	0.990119	1.27697
0.9	1.25	1	240	0.990047	1.16934
0.9	1.25	1.25	130	0.993109	1.12455

On comparison of results from Table 1, it is observed that the best result of field coverage is 0.990003 with CI=1, SI=0.5 and PI=0.9 in 160 generations shown in following figure 1;

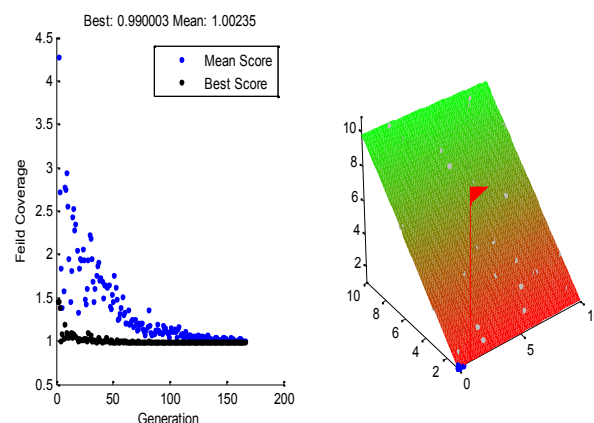


Fig 1: Optimized Field Coverage (FC) parameter

NETWORK ENERGY

The following table shows results of the field coverage by using different values in the parameters;

TABLE 2
RESULTS OF NETWORK ENERGY

Particle inertia	Social interaction	Cognitive Interaction	No of Generations	Best	Mean
0.9	0.5	0.5	160	1.77	1.77191
0.9	0.5	1	205	1.77	1.77156
0.9	0.5	1.25	180	1.77008	1.82438
0.9	1	0.5	160	1.77005	1.80181
0.9	1	1	225	1.77002	1.77626
0.9	1	1.25	240	1.77036	1.77533
0.9	1.25	0.5	140	1.77701	2.34793
0.9	1.25	1	280	1.77001	1.81372
0.9	1.25	1.25	225	1.77011	1.81281

On comparison of the results from Table 2, it is observed that the best result of Network Energy is 1.77000 where CI=0.5, SI=0.5 and PI=0.9 in 160 generations as shown in following figure 2;

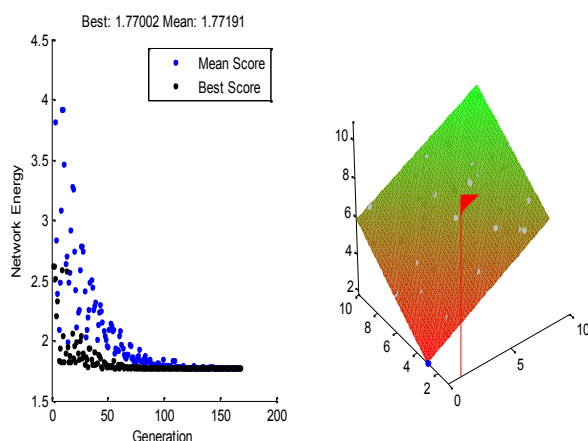


Fig 2: Optimized Network Energy (NE) Parameter

IV. VALIDITY OF PROPOSED SOLUTION

In this study, I have solved the problem by using PSO. The steps of PSO are as follows: I started with initializing the “pbest” variable with some random number and sensor nodes with random velocity and position as there are 100 nodes. Then each node was evaluated by using the fitness function given in equation 3.

Then the fitness value is compared with pbest values, if the sensor’s value is greater than pbest then it is updated with with the current value of the sensor. This process is repeated for each sensor node. Finally, the global best value is found out from the pbest values of all sensor nodes. Then, the updated position of sensor nodes is calculated by using equation 4. This process is repeated till 3000 generations. By analysing these steps, it is proved that it is easier to implement PSO as compared to genetic algorithm. This is because in GA, it is essential to think about many parameters and its evaluation phase consists of complex computation like mutation and crossover.

GA needs to select chromosome to generate the next population but in PSO there is no concept of different populations only the same members are just updated by using simple computation. This thing causes GA to be very slow in execution. One negative point of GA is that when a result constantly appears in proceeding generations, it constantly executes with that result till it reaches at a stall in the generations. However, in PSO once it gets a result which is constantly appearing in proceeding generations it stops at that point. This thing is proved in my study.

A. Comparison of proposed solution with pre-work

Results of optimized parameters of my proposed solution are shown in the above section. These results show that PSO is better than GA.

Field coverage observed in pre-work is about 0.8 (80%) [6] and in my first IS, I proposed an architecture that provided field coverage of about 0.82 (82%) by using GA in 3000 generations but in this study it is observed that the

FC is 0.990003 within 160 generations as shown in figure 1.

The other optimized parameter is network energy and that I have observed around 1.77000 within 160 generations as shown in 2. In the first IS, NE was observed around 0.1.828 in 3000 generations and in pre-work they have observed up to 2.24 [6]. These results prove that PSO produce better field coverage with minimum network energy consumption in less number of generations.

V. CONCLUSION

In this paper, I have used the Particle swarm optimization algorithm based on node placement in wireless sensor networks to improve Genetic algorithm’s results. I have proposed WSN architecture in my first IS which was a modification of the architecture proposed by Bhonekar et al [6] and proved it by using Genetic algorithm. The observed results show that PSO is better than Genetic algorithm. My observed field coverage by using PSO is better than the field coverage analysed by using GA with minimum network energy consumption. Hence, I conclude that by using PSO good field coverage can be achieved by using less network energy in less number of generations.

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