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Wireless sensor network design through genetic algorithm

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Abstract
In this paper, we used WSN design, as a *multi-objective optimization problem* through Genetic Algorithm (GA) technique. We examined the effects of GA parameters including population size, mutation probability, and selection and crossover methods on the design. Choosing suitable parameters is a trade-off between different network criteria and characteristics. Type of deployment, effect of network size, radio communication radius, deployment density of sensors in an application area and location of base station are the WSN's characteristics, which were investigated in this paper. The simulation results of this study indicate that the value of radio communication radius has direct effect on radio interference, cluster-overlapping, sensor node distribution uniformity and communication energy consumption. The optimal value of radio communication radius depends on network deployment density rather than network size and deployment type. Location of the base station affects radio communication energy, cluster-overlapping and average number of communication per cluster head. BS located outside the application domain is preferred over that located inside. In all the network situations, random deployment has better performance compared to grid deployment.

Keywords: *Wireless sensor network, cluster head, genetic algorithm, active sensor, base station.*

1. Introduction

Wireless sensor networks (WSNs) have become an essential part of many applications over the past decades [1]. Compared to computer networks, WSNs are small, cheap but have lower power, limited processing, storage, and radio communication capabilities [2]. Depending on the application, one or more sensors are deployed to perform monitoring, tracking, or surveillance [3]. WSNs are used to monitor complex processes in different areas. They are densely scattered either inside or very close to a phenomenon being monitored [4]. Sensors are usually intended to last for a long period of time, such as months or even years [5]. The network operates when power is available [6].

WSNs have attracted a lot of research attention in the recent years [7]. It offers a rich area of research, in which a variety of multi-disciplinary tools and concepts are employed [8]. Due to economic and technological reasons, most available wireless sensor devices are highly constrained in terms of computational, memory, power, and communication capabilities. It has been the focus of considerable research efforts in the areas of communications (protocols, routing, coding, and error correction), electronics (energy efficiency, miniaturization), and control (networked control systems, theory and applications) [9].

Size of network, radio communication radius, type of deployment, location of base station (BS), and density of deployment are some of the fundamental design issues of WSNs [10]. These issues, such as whether sensor nodes are to be deployed randomly or manually? Whether the location of BS is inside or outside the application area? are to be settled before topology initialization. Some of the most important parameters in WSN design are energy consumption, coverage, connectivity, data redundancy, and radio interference [11].

WSNs have dynamic topology. It varies over time. Design and construction of an efficient topology for WSNs is a multi-objective optimization problem [12]. Optimizing one or more parameters regardless of others may cause negative effects on the performance and lifetime of WSNs. For example, optimizing communication energy consumption directly affects coverage, connectivity and radio interference.

To solve and optimize a complex problem in the real world, different methods such as genetic algorithm [13], ant colony optimization [14], and imperialist competition algorithm [15-16] have been proposed. GA is a very simple and powerful simulation technique to optimize problems based on searching in multi-modal landscape. The main goal in GA is to generate and evolve solutions very close to the optimal solution. It is applied in many different domains such as engineering, computational science, and mathematics. GA is based on natural evolution. It includes different steps such as *initialization*, *fitness calculation,* and application of different operators such as *selection*, *crossover,* and *mutation* [17].

We study WSN design in terms of network size, communication and operation energies, cluster distribution uniformity, radio interference, and data redundancy. In the first part of this paper, we try to tune GA parameters under the framework of our WSN model. In the second part of this paper, we study WSN parameters in terms of network size, communication and operation energies, cluster distribution uniformity, radio interference, and data redundancy and find near optimal values of these parameters based on fine-tuned parameters of GA.

The paper is organized as follows: section 2 deals with WSN design issues, section 3 deals with our WSN model, section 4 deals with GA, section 5 deals with results and discussion, and section 6 concludes the paper.

2. WSN design issues

Energy optimization is one of the most important issues in WSN design [18]. Unlike the wired network, WSN energy resources are much bounded. Sensor nodes are battery powered which have limited capacity and lifetime [19]. Recharge or replacement of sensors' batteries is very difficult or impossible in some cases. When batteries are drained out, sensors are not able to stay alive and function. When some nodes of a WSN fail, the WSN has to reorganize and reroute the messages. Using optimized network topologies and suitable network protocols, WSN's lifetime can be increased from months to years. Increasing the lifespan of WSN is an important design consideration.

By reducing the *radio communication range* and minimizing data processing load in sensors, energy can be conserved in a WSN. More than 20% of sensors' energy is consumed in radio communications [20]. Short radio communication range and limited bandwidth are important goals of WSN design.

Type of deployment is also an important consideration in WSN design [21]. Deployment could be deterministic (where sensors are placed manually) or random (sensors are deployed randomly) [22]. The deterministic method is used for small size networks. Random method is used for larger networks with higher density of node deployment. If any sensor node fails, another close by sensor node compensates for the failure by taking additional work load. The network in such a situation functions with reduced performance.

Network topology determines the way different devices on the network are arranged, and how they communicate with each other [23]. The main motivation behind topology design is to build a network that saves energy and preserves important characteristics such as connectivity, and coverage.

WSN topology is dynamic and changes with time according to the network's conditions. Large scale WSNs are, in general, homogenous and all the sensors have equal capabilities. Selection of suitable topology and implementation of efficient network protocols are other important design challenges. Reducing the transmission power of the nodes needs packet delivery through multiple hops. As the direct communication (single-hop) to the base station (BS) drains battery very quickly, all the sensors use multi-hop communication (hierarchical architecture) with short radio distances [24]. It reduces communication energy consumption and network traffic [25].

In the *hierarchical topology*, the application domain area is divided into some sub-domains which are named clusters. Usually, the sensors with more energy and better geographical positions are eligible to be selected and act as cluster heads (CHs). Total number of CHs is generally in the range 5% to 15% of the number of sensors in the network [26]. The members of a cluster communicate with the BS via CHs, and CHs act as relay nodes to carry on data to the BS via single-hop communication paths.

After data are gathered from the cluster members, preprocessing of data is done in the corresponding CH. The CHs forward preprocessed data to the BS. In large scale WSNs, preprocessing of data in CHs reduce energy consumption and data redundancy. Also, clustering of nodes balances the network traffic load dynamically. Selecting suitable CHs and the way of organizing these clusters are still two basic problems in WSN design.

Lack of connectivity and coverage are two undesirable effects of non-uniform cluster deployment. Generally, it is assumed that all clusters are in circular shape with a cluster radius (R_{CH}). How to find an optimal value of R_{CH} is an important issue, as it determines the number of clusters in a deployment. To determine cluster uniformity, cluster-overlapping is a parameter to measure in a WSN domain.

Radio interference is another issue in wireless communication leading to data inaccuracy and wastage of energy resources [27]. To simulate wireless communication and radio interference of wireless sensors, some radio models are proposed [28]. In the first radio model, it is assumed that the radio channel is symmetric so that the energy required to transmit a message from node A to node B is the same as the energy required to transmit a message from node B to node A. As all the sensors are homogeneous, every sensor node has equal radio capability with the same communication radius (R_{rx}). Optimizing the value of R_{rx} is essential, because it determines the extent of radio interference, accuracy of data communication and network connectivity.

Data redundancy is another important consideration in WSN design [29]. Data redundancy wastes memory space, energy and other network resources [30]. In random deployment, sensors are deployed with high density. The sensing radius (R_{sen}) indicates the maximum sensing coverage area which is monitored by a sensor node. To reduce data redundancy, every CH performs data fusion of the received data from active sensors.

WSNs are designed for *specific applications* and usages. In addition to the important issues such as energy consumption, coverage, and connectivity, some parameters of the specific application should also be taken into account in considering a design.

3. WSN Model

This section describes the WSN model studied and used in the rest of the paper. In our proposed model, we assume that all the sensor nodes are stationary and identical in capabilities. A sensor node can function in two modes: (i) a cluster head (CH), (ii) an active sensor (ACS), depending on the role assigned to a sensor node dynamically. The model deals with radio communication, data sensing, energy consumption, sensor placement, and topology aspects of WSN. Sensor nodes can be deployed manually or randomly in the application area. We use a cluster-based topology with single-hop transmission. It is assumed that remote BS can always communicate with all the sensors directly. CHs are required to communicate over relatively longer distances; therefore, their batteries drain more quickly than those of other sensor nodes. CHs have to gather data from the members of the corresponding clusters, preprocess the data, and forward it to the BS after data fusion.

The main issues in a WSN design are *reducing energy consumption*, optimizing deployment of sensors, reducing radio interference, enhancing network coverage and network connectivity. Radio communication and sensing coverage areas of the sensor nodes are in a circular shape. Every sensor node has a sensing coverage radius (R_{sen}) and radio communication radius (R_{rx}) associated with it. The overlapping of sensing areas, intersection of clusters and overlapping of radio coverage of two sensor nodes can be obtained by Eq. (1).

$$A = 2R^2 \cos^{-1}\left(\frac{d}{2R}\right) - \frac{1}{2} d \sqrt{4R^2 - d^2} \tag{1}$$

where R represents the clusters, sensing or radio communication radii and d is the Euclidean distance between two sensor nodes. Sensor nodes consume energy for sensing, processing, and radio transmission. A major part of energy is used for radio communication. In the first radio model, ACS communicates over short radio distances [26]. Data transmission energy consists of transmitting (E_{Tx}) and receiving (E_{Rx}) energies [30]. Thus, to transmit a k-bit message over a distance of d using the first radio model may be given by Eq. (2).

$$E_{Tx}(k,d) = E_{Tx-elec}(k) + E_{Tx-amp}(k,d) = \begin{cases} k \times E_{elec} + k \times \varepsilon_{fs} \times d^2 & d < d_0 \\ k \times E_{elec} + k \times \varepsilon_{mp} \times d^4 & d \geq d_0 \end{cases} \tag{2}$$

where d_0 is the threshold distance defined as $d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}}$, ε_{fs} is the energy loss to send 1-*bit* message by transmitter amplifying circuit in elemental area in free space model, and ε_{mp} is the energy to send 1-*bit* message by transmitter amplifying circuit in multi-path fading model, $E_{Tx\text{-}elec}$ is the energy spent by the transmit circuit, $E_{Tx\text{-}amp}$ is the energy-cost of the transmission amplifying circuit, $E_{Rx\text{-}elec}$ signifies the energy-cost of the receiving circuit, and E_{elec} is the energy expense to transmit or receive 1-*bit* message by the transmitting or the receiving circuit. The energy spent in receiving data can be given by Eq. (3).

$$E_{Rx}(k,d) = (E_{Rx} + E_{BF}) \times k \tag{3}$$

where E_{BF} is the beam forming energy. Not only do distances transmit, but the number of transmit and receive operations for each message also has to be minimized. The energy consumption for data fusion ($E_{\text{da-fus}}$) is represented by Eq. (4).

$$E_{da-fus}\left(k,d\right) = k \times E_{da} \quad (4)$$

Total energy which a sensor node consumes for communication ($E_{\text{CE-Sen}}$) may be represented by Eq. (5).

$$E_{CE-Sen}\left(k,d\right) = E_{Tx}\left(k,d\right) + E_{Rx}\left(k,d\right) + E_{da-fus}\left(k,d\right) \quad (5)$$

WSN's total energy consumption for communication can be represented by Eq. (6).

$$CE = \sum_{i=1}^{n} E_{CE-Sen_i}\left(k,\ d_i\right) \quad (6)$$

Operation energy (*OE*) is different for different nodes. In the present model, *OE* of a node in CH mode is assumed to be ten units of operation energy and an active sensor consumes two units of operation energy. The exact value of *OE* is related to electro-mechanical characteristics of a sensor node. The *OE* of sensors is calculated by Eq. (7) in this study.

$$OE = 10 \times N_{CH} + 2 \times N_{ACS} \quad (7)$$

where N_{CH} is the total number of CH nodes and N_{ACS} is the total number of ACS.

Network connectivity has to cover all sensor nodes. If an ACS cannot access its CH within its radio coverage, it is disconnected from the network. This sensor node becomes out of range and is represent by ACS_{out}. Total number of out of range sensors (N_{ACSout}) is obtained by counting how many ACS_{out} are there.

Every CH should have some nodes belonging to the cluster; otherwise, it becomes a useless cluster head ($\text{CH}_{\text{useless}}$). In our study, we try to minimize number of useless clusters. The total number of useless cluster heads represented by $N_{\text{CHuseless}}$ is obtained by counting how many $\text{CH}_{\text{useless}}$ are there.

For every CH, a predefined number of nodes are allocated depending on the hardware and communication capabilities of the nodes. If a CH provides services for more than the maximum number of ACSs, it is called an overloaded cluster head ($\text{CH}_{\text{overload}}$). We also assume in our model that every CH can provide services to ten ACSs at most. Total number of overloaded cluster heads ($N_{\text{CHoverload}}$) is obtained by counting how many $\text{CH}_{\text{overload}}$ are there.

4. Genetic Algorithm

Genetic algorithm is a search heuristic which was proposed by John Holland and his students in Michigan University in 1975 [13]. GA does searching through a population of points. A large number of points increase the number of calculations and decrease speed. GA works with coded parameters not with parameters itself. Genes are used to represent the coded parameters. Representing and encoding of parameters in GA can be done in different ways such as binary, decimal or any other base. A predefined collection of genes is named chromosome. GA deals with a population of individuals, where each individual is a potential solution represented as a chromosome. Each population evolves through a number of generations. A fitness function is applied to each member (chromosomes) of the population.

Chromosomes are selected for recombination based on fitness. Better chromosomes have higher chances of being carried to the next generation (elitist). In the crossover step, two different chromosomes (parents) are selected for recombination from which two children are created. To prevent premature convergence to local optima, mutation operator is used. In this set up, WSN design reduces to multi-objectives optimization. This multi-objective optimization is defined by Eq. (8).

$$f = \min\left\{\sum_{i=1}^{9} J_i W_i\right\} \quad (8)$$

J_1 through J_9 represents the objective parameters and W_1 through W_9 represents the weight of each parameter in the objective function (Table 1).

To represent WSN parameters in a chromosome, we use binary encoding scheme: 1 for cluster head and 0 for active sensor. For example, a chromosome '101000…101' means "CH, ACS, CH, ACS, ACS, ACS, …, CH, ACS, CH". The length of every chromosome is determined by the number of WSN's sensors alive. For example, a WSN with 100 sensor nodes alive, the length of every chromosome is 100. We use elitist GA, that is, a chromosome with the highest fitness value is retained in the next generation. The fitness function is defined by Eq. (9).

$$f = \frac{1}{N_{\text{ACS}} \times W_1 + N_{\text{CH}} \times W_2 + \text{CH}_{overlap} \times W_3 + \text{CH}_{overload} \times W_4} \cdots$$
$$\frac{1}{+R_{radio} \times W_5 + OE \times W_6 + CE \times W_7 + \text{CH}_{useless} \times W_8 + \text{ACS}_{out} \times W_9} \quad (9)$$

Based on normalization, the final values of the weighing coefficients of fitness function are determined as shown in Table 2. The final values of the coefficients are trade-off between energy management, and network connectivity.

5.Results and Discussion

In the first part of this paper, we examined the effects of GA-parameters on simulation and

optimization of WSNs under the framework of the proposed model. We first fixed the values of the GA parameters through fine-tuning. To begin the simulation study, we used the values of different GA parameters given in Table 3 and selected a suitable mutation probability based on network size shown in Table 4.
We used five different sizes of the monitoring area: $10m\times10m$, $15m\times15m$, $20m\times20m$, $25m\times25m$, $30m\times30m$. We assumed that the initial values for communication energy were as shown in Table 5.
We optimized the number of cluster head sensors (N_{CH}), subject to optimal number of active sensors (N_{ACS}) for coverage, minimize cluster-overlapping ($CH_{overlapp}$), cluster head overloading ($CH_{overload}$), radio interference (R_{radio}), operation energy (OE), communication energy (CE), cluster without any member node ($CH_{useless}$), and the number of active sensors out of coverage (ACS_{out}).

Table 1. Correspondence between optimization parameters and objectives.

Objective	Optimization Parameter	GA Symbol
J_1	Total number of active sensors	N_{ACS}
J_2	Total number of cluster heads	N_{CH}
J_3	Total amount of cluster heads overlapping	$CH_{overlapp}$
J_4	Total number of CHs overloaded	$N_{CHoverload}$
J_5	Total value of radio interference	R_{radio}
J_6	Total value of operation energy	OE
J_7	Total value of communication energy	CE
J_8	Total number of CH without any member	$N_{CHuseless}$
J_9	Total number of ACSs out of coverage	N_{ACSout}

Table 2. Weighing coefficients of fitness function.

Weights	Up to 25 Sensors	Up to100 Sensors	Up to 225 Sensors	Up to 400 Sensors	Up to 625 Sensors	Up to 900 Sensors
W_1	10^{-4}	10^{-2}	10^{-3}	10^{-2}	10^{-3}	10^{-4}
W_2	10^{2}	10^{2}	10^{2}	10^{2}	10^{5}	10^{7}
W_3	10^{2}	10^{2}	10^{2}	10^{2}	10^{8}	10^{8}
W_4	1	1	1	1	1	1
W_5	10^{2}	10^{2}	10^{3}	10^{3}	10^{-4}	10^{-4}
W_6	10^{4}	10^{5}	10^{6}	10^{7}	10^{10}	10^{10}
W_7	10^{5}	10^{7}	10^{7}	10^{8}	10^{8}	10^{8}
W_8	1	1	1	1	1	1
W_9	1	1	1	1	1	1

Table 3. Initial values for GA parameters.

Parameters	Description	Values
$P_{selection}$	Selection probability	0.07
$P_{crossover}$	Crossover probability	(0.00035×No. of Generation)+0.4465
N_{GE}	Number of generation	500
$N_{population}$	Number of individuals	50
Sel_{method}	Selection method	rank
Cr_{method}	Crossover method	Two-point crossover method

Table 4. Mutation Probability.

Network Size	Probability of Mutation
Up to 25 Sensors	$0.01\times e^{-\frac{\text{No. of Generation}}{1\times\sqrt{\text{Size of Network}}}}$
Up to 100 Sensors	$0.01\times e^{-\frac{\text{No. of Generation}}{3\times\sqrt{\text{Size of Network}}}}$

Up to 225 Sensors	$0.01\times e^{-\frac{\text{No. of Generation}}{5\times\sqrt{\text{Size of Network}}}}$
Up to 400 Sensors	$0.01\times e^{-\frac{\text{No. of Generation}}{5\times\sqrt{\text{Size of Network}}}}$
Up to 625 Sensors	$0.01\times e^{-\frac{\text{No. of Generation}}{6\times\sqrt{\text{Size of Network}}}}$
Up to 900 Sensors	$0.01\times e^{-\frac{\text{No. of Generation}}{7\times\sqrt{\text{Size of Network}}}}$

Table 5. Initial values for communication energy.

	Description	Values
R_{sen}	Sensing coverage radius	$5m$
E_{Tx}	Transmission energy	$50nJ/bit$
E_{Rx}	Receiving energy	$50nJ/bit$
E_{BF}	Beam forming energy	$5nJ/bit$
E_{da}	Energy consumption for data fusion	$5pJ/bit$
ε_{amp}	Transmitter amplifier energy	$100pJ/bit$
ε_{fs}	energy to send 1-bit message by transmitter amplifying circuit in elemental in free space model	$10pJ/\text{bit}/m^2$
ε_{mp}	energy to send 1-bit message by transmitter amplifying circuit in multi-path fading model	$0.0013pJ/bit/m^2$

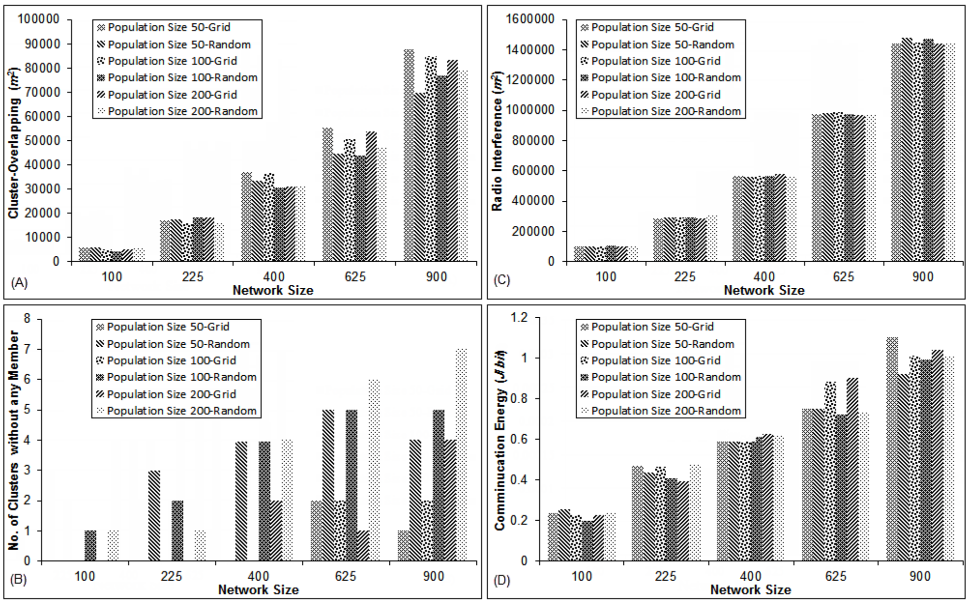

Figure 1. Cluster-overlapping (A), no. of clusters without any member (B), radio interference (C), and communication energy (D) versus network sizes with different population sizes.

To study the effect of population size, we did simulation with three different sizes of population 50, 100, 200 for different network sizes and deployments. Increasing or decreasing the number of chromosomes in the population does not affect cluster-overlapping (Figure 1A), radio interference (Figure 1C) and communication energy (Figure 1D). The number of member-less cluster heads depends on the type of network deployment. Compared to grid deployment, we find more cluster heads without any member in random deployment, which increases with the increasing size of the network (Figure 1B). Deciding an appropriate population size is a trade-off between WSN and GA parameters. Increasing the number of chromosomes in the population increases the CPU time.

To study the effect of selection methods in GA, we used two selection methods: rank and tournament with different type of deployments and WSN sizes. Figure 2(A) illustrates that the tournament selection has lower value of communication energy compared to the rank selection for random and grid deployments when the size of network is small.

With larger size networks, the rank selection has lower value of communication energy compared with the tournament selection for random and grid deployments. The rank selection has lower value of cluster-overlapping compared with the rank selection for random and grid deployments in all of the network sizes (Figure 2B). Compared with the rank selection, tournament selection has lower radio interference in all the sizes and types of networks shown in Figure 2(C). By using rank selection, we can minimize operation energy for all the network sizes and deployment types (Figure 2D). We use rank selection for the sake of energy minimization. Energy optimization in a WSN increases the network lifetime and improved the network coverage for small sized networks with tournament selection. When the size of a network is large, rank selection gives better results.

To study the effect of crossover method in WSN design, we used one-point and two-point crossover methods.

We use variable probability of crossover, $P_{crossover} = (0.00035\times\text{No. of Generation}) + 0.4465$. Compared with two-point crossover, one-point crossover is more effective in minimizing the value of cluster-overlapping (Figure 3A). Type of crossover does not affect the communication energy; the values of communication energy are very close as shown in Figure 3(B). Network radio interference is minimized with two-point crossover compared with that of one-point crossover shown in Figure 3(C). Figure 3(D) indicates that the type of crossover does not affect $CH_{useless}$, but it depends on the size and type of deployment in the network. Since two-point crossover gives better results than one-point crossover, we use two-point crossover for the rest of the study.

Mutation is an important step in GA. A small change in mutation probability affects the result strongly. To study the effect of mutation probability in WSN design, we use (i) probability of mutation constant ($P_{mutation} = 0.001$), and (ii) exponential probability of mutation varying with the generation number and the network size.

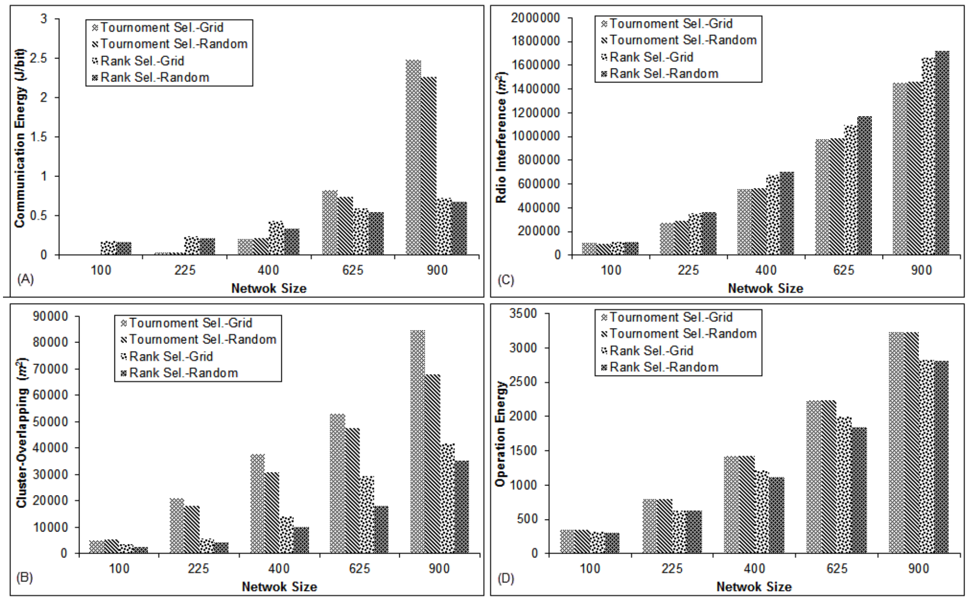

Figure 2. Communication energy (A), cluster-overlapping (B), radio interference (C), and operation energy (D) versus network sizes under different selection methods.

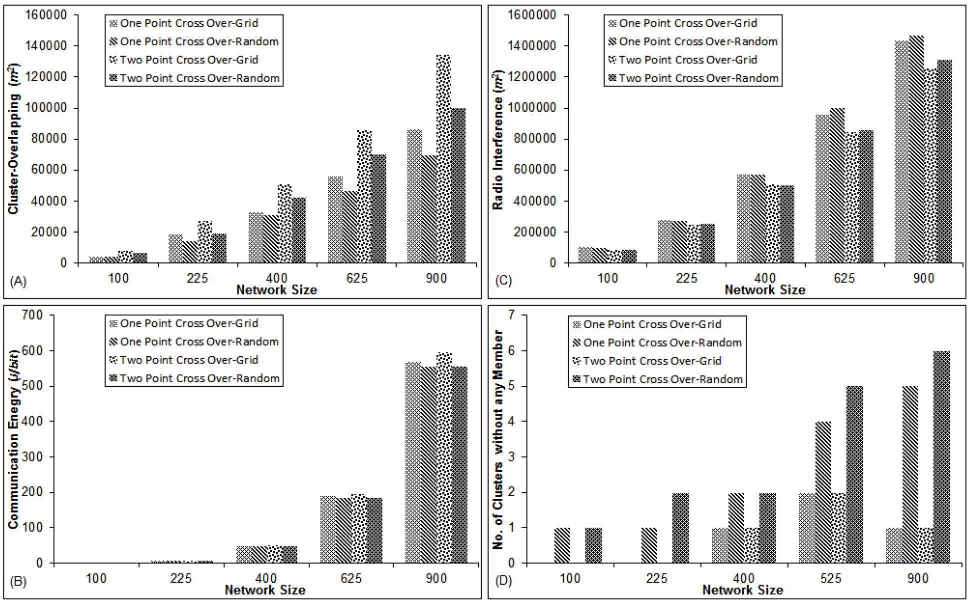

Figure 3. Cluster-overlapping (A), communication energy (B), radio interference (C), and no. of clusters without any member (D) versus network sizes for different crossover methods.

When the mutation probability is changed, the fitness function weights are tuned again. Table 2 shows the fitness function weights for exponential mutation probability and Table 6 shows the different values of the fitness function weights for constant mutation probability.

Figure 4(A) shows that variable probability of mutation is more effective in optimizing cluster-overlapping in both deployment types and sizes of network compared with those with constant probability of mutation. Mutation probability does not affect the average number of communications per cluster (Figure 4B).

Constant probability gives better performance in radio interference compared with variable probability (Figure 4C).

Using variable probability, one can better optimize the communication energy of networks of different types and sizes (Figure 4D). Using exponential mutation probability leads to cluster deployment uniformity, increases in network coverage and lifetime optimization of network communication energy consumption, and decreases in network radio interference.

For finding optimal WSN design parameters and minimizing CPU time, we use *population of size* 50, *rank* selection, *two-point* crossover, *variable* probability of *crossover*, and *exponential* probability of *mutation*, which changes with *generation* for *random* and *grid* deployments.

Radio communication radius (R_{rx}) is dependent on the characteristics of WSNs such as *hardware limitation*, *density*, *deployment*. It is optimally fixed with respect to *network connectivity*, and *radio interference*. When the value of R_{rx} is decreased, the network connectivity goes down as well. Increasing the value of R_{rx} leads to more consumption of network energy.

Table 6. Weighing coefficient of fitness function for constant mutation probability.

Weights	Up to 25 Sensors	Up to100 Sensors	Up to 225 Sensors	Up to 400 Sensors	Up to 625 Sensors	Up to 900 Sensors
W_1	10^{-4}	10^{-2}	10^{-3}	10^{-2}	10^{-3}	10^{-4}
W_2	10^{-2}	10^{4}	10^{6}	10^{6}	10^{7}	10^{8}
W_3	10	10^{2}	10^{3}	10^{4}	10^{8}	10^{8}
W_4	1	1	1	10^{2}	1	1
W_5	10^{3}	10^{2}	10^{2}	10^{2}	10^{-2}	10^{-4}
W_6	10^{5}	10^{5}	10^{7}	10^{9}	10^{10}	10^{10}
W_7	10^{5}	10^{5}	10^{5}	10^{6}	10^{8}	10^{9}
W_8	1	10^{2}	10^{2}	10^{2}	1	1
W_9	1	1	1	10^{2}	1	10^{2}

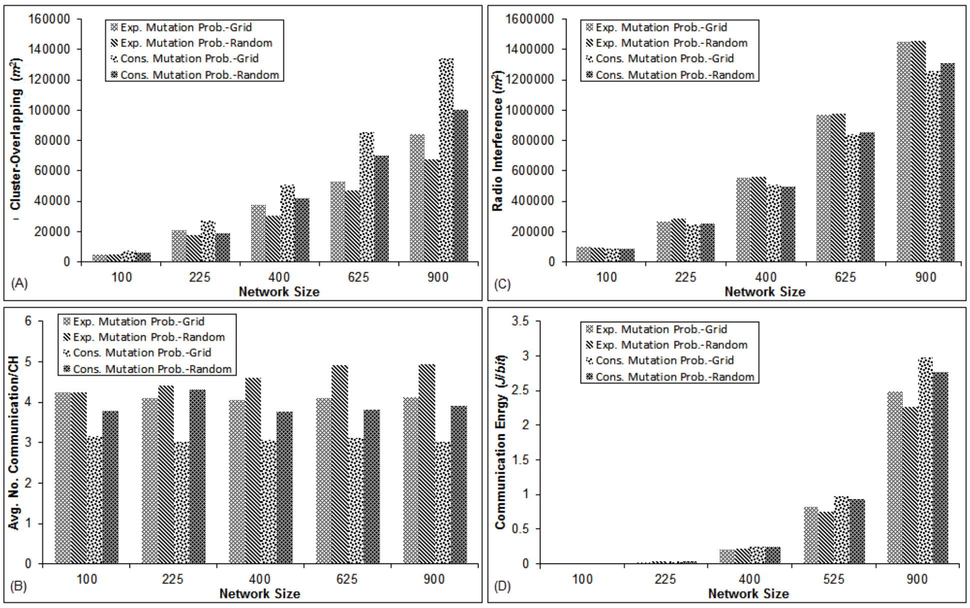

Figure 4. Cluster-overlapping (A), avg. no. of communication/CH (B), radio interference (C), and communication energy (D) versus network sizes for different mutation probabilities.

The simulation results shown in Figure 5 indicate that irrespective of the network size and deployment, the optimal value of R_{rx} is 5 *m* for the proposed WSN model (Figure 5A), and increasing the value of R_{rx} increases radio interference (Figure 5B), and decreasing its value increases the number of sensors out of range affecting connectivity (Figure 5A).

To study the effect of deployment on WSN design, we studied two types of deployment: *grid* and *random* for five network sizes. *Radio interference* in random deployment is less than that of the grid deployment shown in Figure 6(A). The value of *operation energy* in random deployment is much lower than that of grid deployment when the size of the network is small. When the size of the network is increased, these values are very close shown in Figure 6(B).

Clusters in the network with grid deployment are more *flexible* and have *better cluster distribution uniformity* compared with that of random deployment when the size of the network is small, but by increasing the size of the network, clusters with random deployment become *more flexible* and have *better uniformity* in *cluster distribution* compared with that of grid deployment shown in Figure 6(C).

Grid deployment requires more *communication energy* than random deployment shown in Figure 6(D). Thus, WSN with random deployment *lasts longer* than a WSN of equal size with a grid deployment.

In WSN design, location of the BS can be *inside* or *outside* of an application area. Figure 7(A) illustrates that outside located BS *reduces* the value of *cluster-overlapping* compared with BS located inside. Therefore, *clusters* in a WSN with outside located BS are *distributed more uniformly*. The average number of communications per cluster for all network sizes and types are *equal* when the BS is located inside. It is less than those in the cases when the BS is located outside. It means that the network can be designed with *less number* of CHs when the BS is *located outside* (Figure 7B). But with inside located BS, the radio interference is lower than outside located BS for all different network types and sizes (Figure 7C). *Outside* located BS affects the value of *communication energy* of the network (Figure 7D).

To study the effect of density, we define *unit* density as *one sensor* per *meter* because the R_{sen} is 1 meter. We experiment with three different densities: 0.5, 1 and 1.5.

If the area size is 100 m^2, we deploy 50 (density is 0.5), 100 (density is 1) and 150 (density is 1.5) sensors in the area. *Radio interference* (Figure 8A), cluster-*overlapping* (Figure 8B), and the *number of clusters without any member* (Figure 8D) all increase with *increasing* density of deployment, but the number of *active sensors out of range* (Figure 8C) *decreases*.

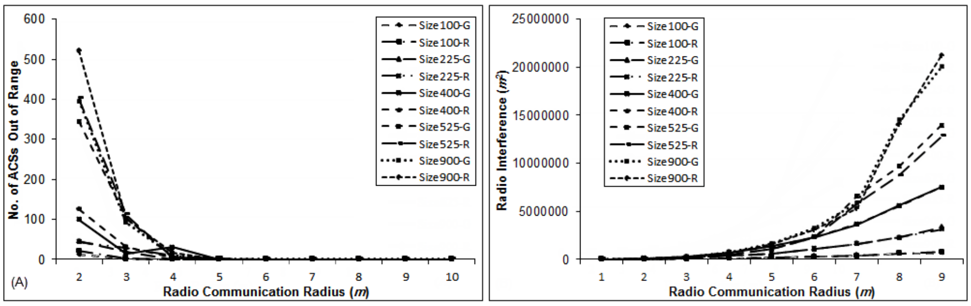

Figure 5. No. of ACSs out of range (A), and radio interference (B) versus radio communication radius.

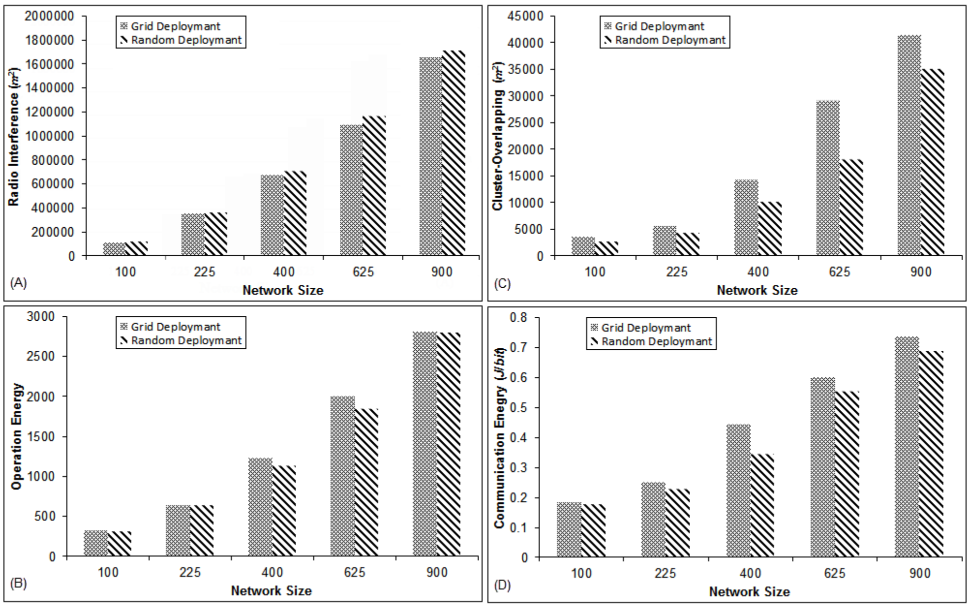

Figure 6. Radio interference (A), operation energy (B), cluster-overlapping(C), and communication energy (D) versus network sizes under grid and random deployments.

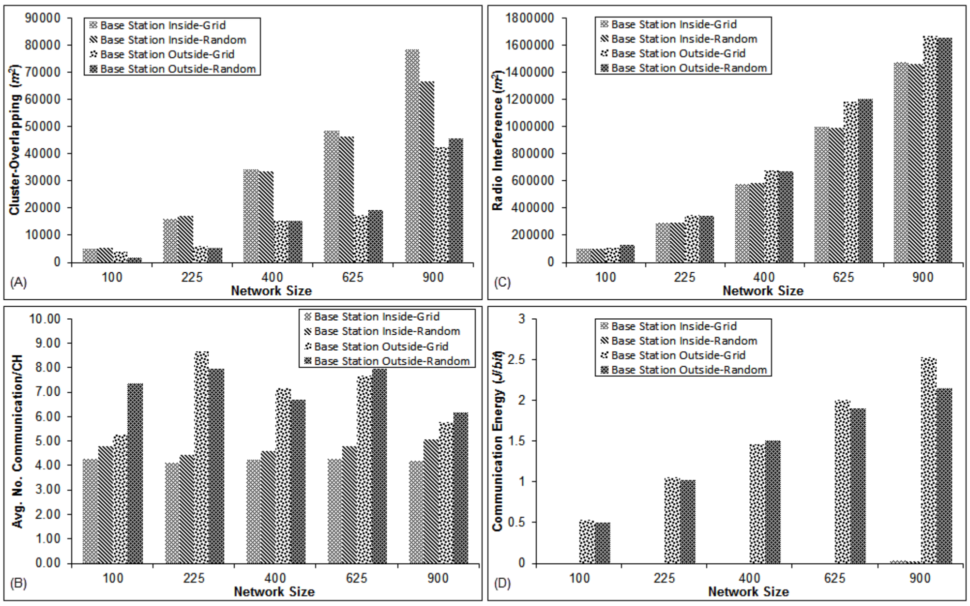

Figure 7. Cluster-overlapping (A), avg. no. of communication/CH (B), radio interference (C), and communication energy (D) versus network sizes for two possible locations of BS.

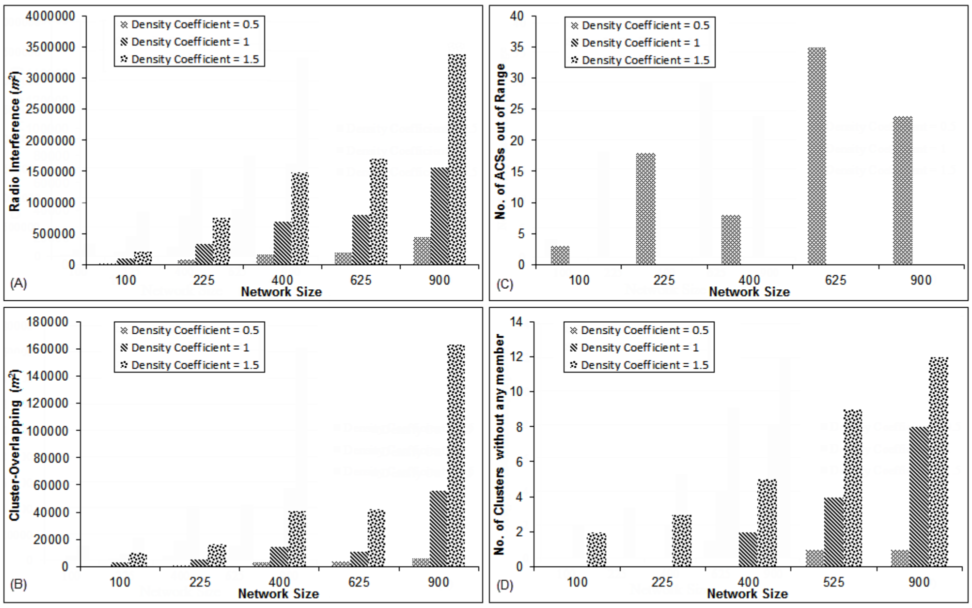

Figure 8. Radio interference (A), cluster-overlapping (B), no. of ACSs out of range (C), and no. of clusters without any member (D) at different densities.

6. Conclusion

We study WSN design through GA by first studying and fixing the GA parameters and then using these values for near optimal WSN design. There are trade-off among different criteria and parameters of WSNs. The algorithm is coded in MATLAB version 7 on Intel® core *i*5 CPU 650 3.2 *GHz* running Windows 7 professional. With increasing sizes of network, optimization time increases.

The simulation results of this study indicate that deciding an appropriate population size is a trade-off between WSN parameters and GA parameters. In small sized networks, to optimize energy, to increase the network's lifetime and to improve the network's coverage, tournament selection is more efficient. When the size of a network is large, rank selection has better performance. Also, two-point crossover's performance is better than one-point crossover for the proposed model. Exponential mutation probability increases a network's coverage and lifetime, and decreases network communication energy consumption and radio interference.

By increasing the size of a network, optimization time is increased. The simulation results of this study indicate that the value of radio communication radius directly affects radio interference, cluster-overlapping, and uniformity in distribution, communication energy, and number of sensors out of range and CHs without any member. The optimal value of radio communication radius is not dependent on network size and type of deployment, but dependent on the density of network deployment. Outside located BS reduces the value of cluster-overlapping compared with the case when the BS is located inside.

The average number of communications per cluster for all network sizes and types are equal when the BS is located inside. With inside located BS, radio interference value is lower than when the BS is located outside for all deployments and sizes. Outside located BS affects communication energy. Outside located BS is preferred over inside located BS. Sensing radius determines density of a network. Density affects radio communication radius strongly. In all the network situations, random deployment has better performance compared with grid deployment. Future research will focus on WSN design using other optimization methods.

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