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Multi Objective Genetic Algorithm (MOGA) Optimized Clustering Probability Approach for Wireless Sensor Network

Avantika Goyal
M. Tech. Scholar
Department of Electronics & Communication Engineering
Lakshmi Narain College of Technology, Indore (India)
g.avantika24@gmail.com

Praveen Patidar
Asst. Professor
Department of Electronics & Communication Engineering
Lakshmi Narain College of Technology, Indore (India)
praveenkpatidar@gmail.com

Abstract –**Sensor nodes in wireless sensor networks (WSN) are powered with a battery. Sensor nodes consume the battery power mainly in the tasks like data transmission, data reception and sensing. Sometimes it is impractical to replace a battery in WSN because humans can't reach. Therefore once energy or computational resources are consumed, immediate recovery of these resources is a complex task so it is necessary to make use of battery power efficiently to increase the lifetime of the sensor nodes that will also increase the lifetime of the whole network. To make WSN energy efficient and to increase the lifetime of the network we design a Multi-Objective Genetic Algorithm (MOGA) optimized clustering probability so as to find a method which increases the lifetime and reduces the energy consumption of the network. The execution and demonstration of this work is performed with the help of MATLAB 2014a. The performance comparison metrics are; network lifetime, network throughput and number of alive nodes.**

Keywords –**LEACH, MOGA, Pareto-Optimality, WSN.**

I. Introduction

Wireless Sensor Networks (WSN) is a network formed by a large number of sensor nodes where each node is equipped with a sensor to detect physical phenomena such as light, heat, pressure, etc. WSNs are considered a revolutionary method of gathering information to build the information and communication system that will greatly improve the reliability and efficiency of infrastructure systems [1-2].

Each node in a wireless sensor network (WSN) is resource constrained: node have limited power, speed of processing, capacity to store data, and communication bandwidth [3]. After their deployment in the target area they are responsible for self-organizing an appropriate network infrastructure [4-5]. Global Positioning System (GPS) and local positioning algorithms are used to obtain location of the sensor nodes [6].

Wireless Sensor Network nodes are densely deployed in the target area and the power is provided to them via battery which is the only source of energy for most of the sensor nodes. Sometimes this target area is not reachable by the humans so it is impractical to replace a battery therefore once energy or computational resources are consumed, immediate recovery of these resources is a complex task. This is the reason why a large part of the research in WSN focuses on the development of energy efficient or economical method for WSN [7].

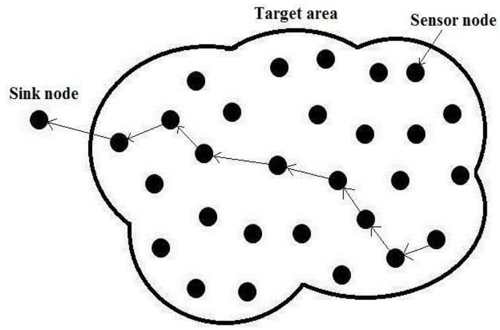

Figure 1: Wireless Sensor Network [7]

WSN consist of large number of sensor nodes that are deployed in the environment and are powered by battery and replacing the battery of each and every node in the sensor network is impractical so it is necessary to make use of this limited energy efficiently therefore an energy efficient algorithm has to be designed. The nodes in the WSN are distributed spatially and to send the sensed data to the base station or sink node needs multi-hop communication when the base station or sink is not

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in range so the number of intermediate nodes are required to send this sensed data to the desired destination which consumes more energy of the network because all the intermediate nodes forward the data coming from their neighbour and to do this job they consume energy and this motivate us to reduce the number of hops and intermediate nodes taking part in transmission of data by using clustering algorithm in which the nodes are grouped into clusters and each node in cluster send data only to their concerned cluster head which is then aggregate all the data coming from the member nodes and send it to the sink or base station.

The energy efficient nature, data aggregation, load balancing, and improved network lifetime of hierarchical cluster based routing motivate us to use them for this research. These protocols are centralized or distributed depends on the process of selecting cluster heads. The location of each and every node in the cluster and their residual energy are used to make decision for selecting one of them as a cluster head one such protocol is LEACH. The LEACH protocol is chain based protocol in which each node communicates only with its previous and next neighbour and reduces the number of communicating nodes which helps in reducing energy consumption.

Although there is a drawback of using fixed cluster head because all the data of member nodes are routed through the cluster head which lead to higher energy consumption at cluster head and due to this reason they die soon but it will also improve the life time of the network. Increasing the size of cluster head or providing more power as compared to the member node will increase their lifetime. Hence to increase the lifetime of the network and to make it energy efficient the best approach is hierarchical based clustering.

II. Proposed Method

A. *Low-Energy Adaptive Clustering Hierarchy (LEACH)*

During the configuration phase, randomly generated cluster head, the random number is selected in a range between 0 and 1 in each sensor node, if the selected number is smaller than some threshold $T(n)$, then the node is selected as the head of the cluster. Formulas of $T(n)$ as follows [8]:

$$T(n) - \int_0^n \frac{p}{1-p\left[r \bmod \left(\frac{1}{p}\right)\right]} \quad \text{with } n \in G \qquad (1)$$

Where, p is the percentage of the number of cluster headers and the total number of nodes in the network, r is the number of the current round, G is the set of cluster nodes except the cluster head of the last rounds $\frac{1}{p}$. Then, the header node of the cluster transmits the message that it is becoming a cluster head in the entire network, each node decides to join that cluster according to the intensity of the received information and responds to the corresponding cluster header. Then, in the next phase, each node uses the TDMA method to transmit data to the cluster header node, the cluster head sends the fusion data to the receiving node. Among the clusters, each cluster competes with the communication channel with the CDMA protocol. After a period of stable phase, the network enters the next round of the cycle again, continuous cycle.

B. *MOGA-Optimized Cluster Head Election Probability*

Let n_{alive} represents the number of alive nodes with residual energy greater then the threshold energy and p be the clusterhead election probability, then the optimum number of CH elected for a given round will be:

$$P_{opt} = n_{alive} * p \qquad (2)$$

Here P_{opt} is optimized using Multi-Objective Genetic Algorithm (MOGA), which is described as follows.

Multi-Objective Genetic Algorithm (MOGA)

Let an individual x_i at the generation t, dominated by P_{opt} individuals. The rank of this individual is:

$$Rank(x_i, t) = 1 + P_{opt} \qquad (3)$$

All non-dominated individuals are rank 1.

The adaptation of genetic algorithms to multi-objective optimization is mainly done at the level of the evaluation step of the effectiveness of a solution which is then divided into two stages:

- Evaluation of the effectiveness of the solution in terms of convergence.
- Evaluation of the solution's effectiveness in terms of diversification.

The diagram of the genetic algorithm with addition of its phases is represented in (Figure 4.2). Step 2a corresponds to the calculation of the efficiency with respect to the convergence and step 2b corresponds to the calculation of the diversity of the solution. The main mechanisms used for these tasks are presented in the following subsections. It should be noted that according to the mechanisms used it is possible to obtain two different efficiencies for the same solution one for the convergence and the other for the superimposition. It is then necessary to take this fact into account in the selection phase when it is a question of comparing two solutions. Another mechanism, elitism is presented in this section.

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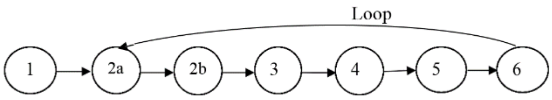


Figure 2: Stages of a multi-objective genetic algorithm [36]

The steps of the multi-objective genetic algorithm are the same as those of (Figure 2). The step divided into two sub-steps the first (2a) corresponds to the assessment of the quality of the solution in terms of convergence and the second (2b) corresponds to the assessment of the quality of the solution in terms of the diversity.

1. Initialization of the population.
2. Selection.
3. Crossover.
4. Mutation.
5. Replacement [9].

1) Multi-Criteria Selection

The problem is to select individuals but taking into account several criteria instead of one. It is considered that the basic technique of combining all criteria into a weighted sum does not adequately address this problem. It is therefore necessary to adapt the selection operators. A first method consists in selecting in turn the individuals on each of the criteria. But it is even more efficient to use the notion of Pareto-optimality. This notion of pareto optimality makes it possible to establish a relationship of dominance between individuals on several criteria, where only two individuals confront each other, the finally selected individual will be the one who dominates the other in the sense of pareto. The order induced by Pareto optimality being partial, it may be impossible to decide whether one individual dominates the other. In this case, it is necessary to use more advanced techniques one can choose, for example, to select only the non-dominated individuals. However, if it is necessary to set an order on individuals, then several approaches are possible. For example, we can use rank dominance for which we take into account the number of individuals dominating an individual. Other approaches use the depth of dominance, in which case the population is divided into several fronts, each corresponding to the set of individuals being dominated by no other. Finally, another technique is to use the number of individuals dominated by a certain individual. Uncontrolled individuals can then be ordained among themselves [9].

2) Assignment of Effectiveness

The idea of calculating the efficiency of an individual using Pareto dominance was introduced by Goldberg. In general we speak about the rank of the individual. Several approaches have been proposed to assign a rank to different solutions. The first technique consists in attributing to each solution a rank of dominance which corresponds to the number of solutions in the population which dominates the individual. The rank of an individual is then equal to the number of individuals in the population that dominates it plus one. This technique is used in particular by the algorithm of Fonseca and Flemming [10].

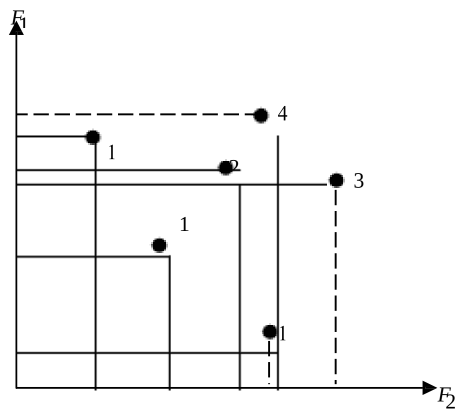
Another possibility is to assign a depth of dominance. It is a question of dividing the population into several fronts and the rank of a solution corresponds to the depth of the front to which it belongs. The rank of an individual is calculated by the algorithm. Individuals dominated only by solutions of E_1 receive rank 2 and form the set E_2. In general, an individual receives the rank k only if he is dominated by individuals of the population belonging to the $E_1 \cup E_2 \cup \ldots \cup E_{k-1}$ set, which is notably used in the NSGA II algorithm.

A final possibility, the dominance count consists in counting the number of solutions that an individual dominates this measure does not immediately give information on the effectiveness of the solution and must be used, like what is done in SPEA and SPAE2, in conjunction with another technique.

The different techniques are illustrated in Figure 3, their interest compared to scalar or other methods is that they make it possible to evaluate the effectiveness of a solution compared to the whole population and that they are unaffected by the shape or continuity of the Pareto border [11].

3) Preservation of Diversity

The methods presented previously tend to favour the convergence towards the optimal Pareto front by favouring the individuals who are little or not-dominated. However, these methods are not able to guarantee that the approximation obtained will be of good quality.



Dominance rank

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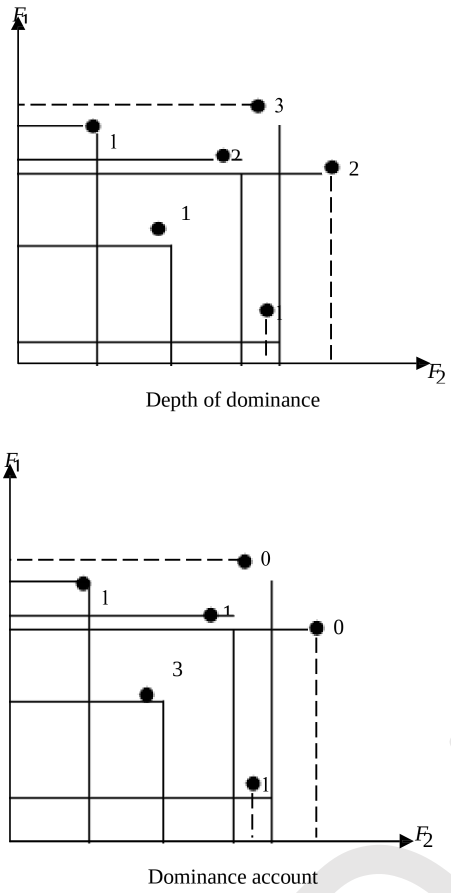

Figure 3: Assignment of efficiency from a dominance point of view

In terms of diversification. Thus genetic algorithms incorporate methods that evaluate the diversity of a solution compared to other solutions of the population. The different approaches take into account a notion of neighbourhood that can be defined in three different ways as suggested by Ziztler et al. [12], the three categories are based on those used in statistical density estimation.

The kernel methods define the neighbourhood of a solution i with respect to a function K which takes as a parameter the distance d_{ij} between i and the other points j are computed and the sum of $K(d_{ij})$ carried out this sum represents the density around the individual i the fitness sharing used especially in MOGA, NSGA and NPGA is certainly the most popular technique in evolutionary algorithms.

The nearest neighbour techniques calculate the distance between a given point and its nearest neighbour to estimate the density in its neighbourhood. This technique has been used in particular in SPEA 2.

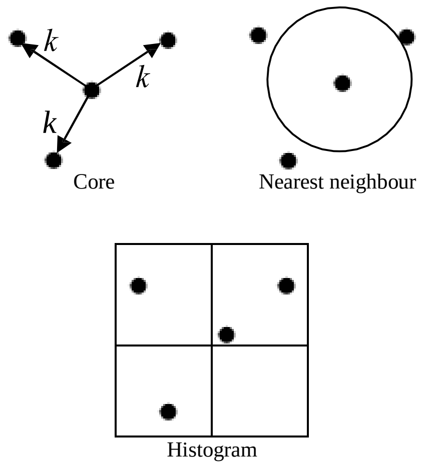

Figure 4: Illustration of techniques for preserving diversity

A third category uses histograms, in this technique the space is divided into neighbourhoods by a hypergrid. The density around a solution is estimated by the number of solutions in the same grid cell. This technique has been used in PAES.

The different approaches are illustrated in Figure 4, for all these methods it is necessary to define a metric that can be calculated on the genotype and / or phenotype in the decision space and / or in the objective space [11].

4) Elitism

The elitist strategy is to keep the best individual in each generation. Thus elitism prevents the best performer from disappearing during selection or his right combinations are affected by the crossing and mutation operators. After each assessment of the performance of individuals at a given generation, the best individual of the previous generation $(t-1)$ is reintroduced into the population if none of the individuals of the generation t are better than him. By this approach, the performance of the best individual of the current population is monotonous from generation to generation. It appears that elitism greatly improves the performance of the genetic algorithm for some classes of problems, but can degrade them for other classes, by increasing the rate of premature convergences.

The multi-objective genetic algorithm (MOGA) has been successfully applied to system control problems, for example: controller of a MIMO system and optimization of parameters, control of systems by the H_∞ command.

MOGA is an evolutionary algorithm that uses the following operators:

- Pareto-Optimal rank.
- Fitness Sharing.
- Mating Restriction.

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- Selection, crossover and mutation.

The philosophy of MOGA is to develop a population of Pareto solutions optimal or close to Pareto optimal throughout the optimization process [13].

In MOGA, the initial population is randomly selected in a defined margin and then decoded (in case of a non-real chromosome). And then evaluated each individual's initial population by a set of objective function values. Then the sequence of the genetic operators is applied, having a result for the next generation, noting that the task of assigning fitness is a more refined and important process (see the shaded area in Figure 5).

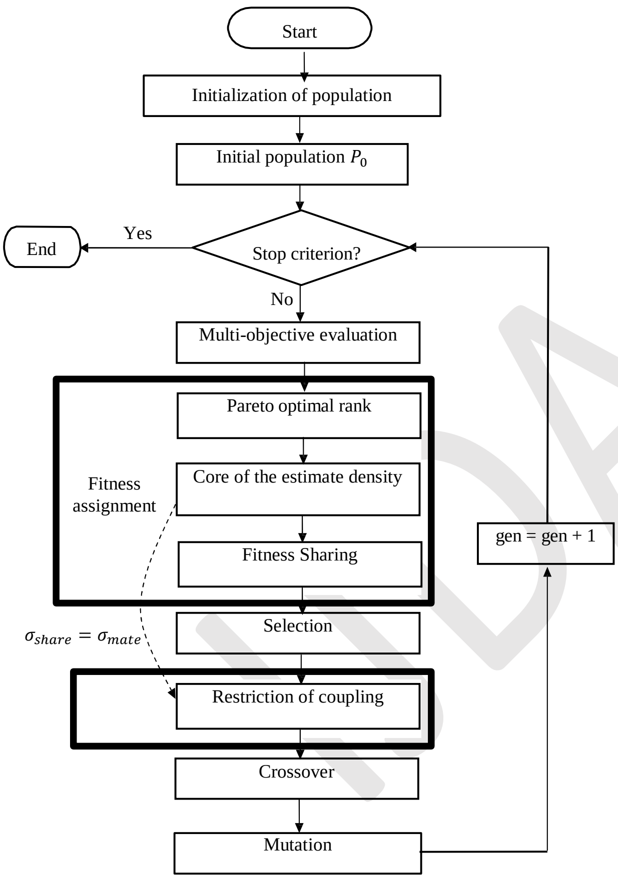

Figure 5: Flow diagram for Multi-Objective Genetic Algorithm

5) Pareto-Optimal Rank

In the absence of information about the importance of objectives, Pareto dominance is the only method of determining performance evaluation. So all Un-controlled individuals are considered the best individuals and so are assigned the same fitness, for example zero. However, determining a fitness value for dominated individuals is a more subjective issue. Individuals are arranged in a goal vector and preference is made (goal, priority). Consideration of purpose and selective priority excludes goals according to their priorities and if they reach their goals, priority and goal information can often be extracted directly from the problem description. Priorities are integer values that determine which order of goals should be optimized, according to their importance. Frequently in the control of systems, closed-loop stability has the highest priority and it is first of all to minimize the goal values indicate the desired level of performance in each goal dimension. The goal vector traces the region of the exchange where MOGA concentrates its computation effort. Once rank is sorted, this genetic operator will assign fitness to individuals by interpolating from best to worst, according to an exponential rule. So a single fitness value is derived for each group of individuals with the same cost, using the average.

6) Fitness Sharing and Core of the Estimation Density

Although the population can potentially search for many local optimums, a finite population will tend to evolve towards a small area of the search space even if other equivalent optima exist. This phenomenon is known by genetic migration. A remedy for this problem proposed by Fonseca and Fleming (1995) with the fitness sharing. It is a technique involving the estimation of the population density, at the points defined by each individual. A suitable σ_{share} niche size was developed by Fonseca and Fleming by using a similar method by density estimation known as the Epanechnikov kernel, is used to penalize individuals according to the proximity of other individuals [14].

7) Niche Technique

This technique allows the exploration of distinct regions that constitute local optimums. In practice, the detection of different solutions gives the engineer the possibility of a final choice not only from the predefined objectives, but also for example from the ease of construction of one or the other solution. We propose to compute niche indices, or resemblance, in the domains of objectives (N_{obj}) and parameters (N_{par}), so as to take into account both domains. These indices are the distances between individuals taken in the order of the values of each objective. The genetic selection operator will work with these clues, not with the assessments of the problem. The goal is to detect distinct niches (in the parameter space), that is, to detect local and / or global optimums in a multimodal problem.

The process consists of two steps. First, for each objective k, we put the population in ascending (or decreasing) order according to the objective analyzed (we must save a vector that indicates the

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initial order) and we compute the distances between the individuals in the two spaces, N_{objk} and N_{park}, in relation to the established order. The second step is to join two similarity indices by a transfer function [12].

8) Mating Restriction

This restriction issue is to keep the diversity along the compromise surface, this avoids an arbitrary combination of pairs outside a given distance of σ_{mate} ABCD that could lead to the formation of a large number of incapable generation. The distance is usually $\sigma_{mate} = \sigma_{share}$. In addition, population diversity is promoted by applying a mutation operator to a limited number of existing individuals. The optimal Pareto approximation is particularly difficult because it is unknown. The traditional way is to experiment and decide by using knowledge a priori or by competing with the results of other methods if the available Pareto front is improving towards Pareto optimal. In general, attention must be paid by using evolutionary algorithms. Even if a good choice of parameters is found for a particular application; this set will be suboptimal for many other problems. Achieving the wrong choice of parameters can produce excessively poor results [12].

III. SIMULATION AND RESULTS

The performance of proposed algorithms has been studied by means of MATLAB simulation.

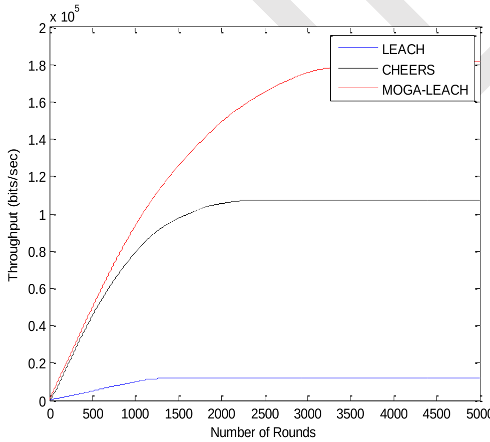

Figure 6: Network throughput comparison for different methods

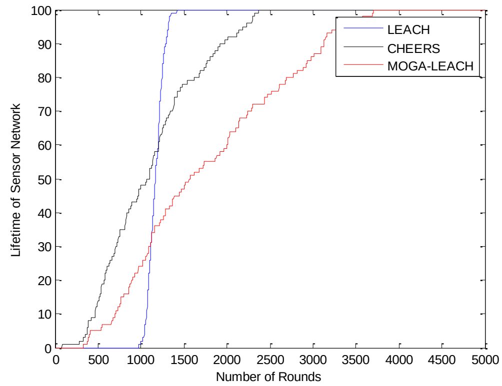

Figure 7: Network lifetime comparison for different methods

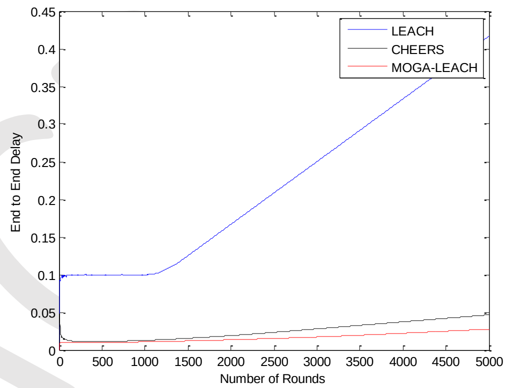

Figure 8: End-to-End delay comparison for different methods

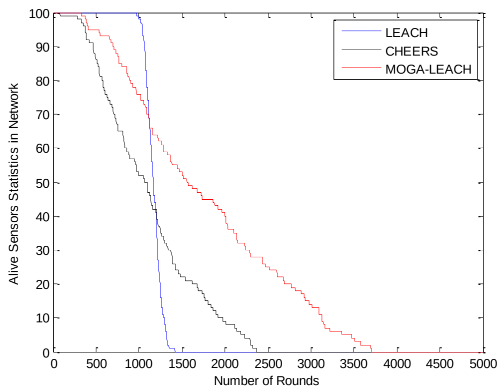

Figure 9: Comparison for number of alive nodes in different methods

IV. CONCLUSION

Under the conclusion of this work, several points were taken under consideration. For better understanding of our work that is evaluation of routing protocols for wireless sensor network. We have framed our work in two scenarios which consist of a simple WSN protocols, for now we have taken LEACH protocol in consideration and performed a comparative study by implementing various topologies.

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Genetic algorithms seem to be an interesting solution to solve the problem of multi-objective optimization. This paper shows the principles and interest of GAs in search of the Pareto-optimality for a multi-objective optimization problem.

The proposed protocol uses Multi-Objective Genetic Algorithm Optimization to optimize the clusterhead election probability. This system accepts three input parameters, which are the residual energy, centrality and distance to base station. The simulation results show that the proposed algorithm extends the network lifetime when the last node dies relative to the CHEERS approach given by Murtaza et al. [8].

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