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EVOLUTIONARY APPROACH TO CLUSTERING IN WIRELESS SENSOR NETWORKS: A REVIEW

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ABSTRACT

Wireless sensor network (WSN) is set of interconnected senor nodes used for communication and data aggregation applications. WSNs are ever evolving networks and Lifetime of sensor nodes is most important parameter in WSN. Optimized usage of network and load balancing helps increase lifetime of network nodes. Clustering is one such technique which helps in efficient organization of networks and energy optimization of the nodes. Over the time, plethora of clustering algorithms has been proposed. Of various proposed clustering algorithms, evolutionary algorithms have been found to give best results. A comparative study of different decentralized evolutionary clustering algorithms used in wireless sensor networks has been elaborated in this paper. All previous proposed evolutionary approaches have been reviewed. Though good optimization results have been achieved using evolutionary algorithms for dynamically evolving WSNs energy efficient clustering protocol is needed. In most of current approaches distance and energy have been focused for optimization. Hybrid evolutionary algorithms for clustering, where dynamics of network such as more communication intensive routes, average time duration could be considered along with energy and distance parameters.

1. INTRODUCTION

Wireless sensor network [1] is an active area for research due to its potential applications in all fields. WSN was first inspired by the US military for enemy surveillance and object tracking [2]. It comprises of interconnected low-power multi-functioning sensor nodes operating in an unattended environment equipped with computational and sensing capabilities. Additionally, each sensor node consists of a wireless radio transceiver, a small microcontroller and an energy source, usually a battery. Sensor nodes are implemented as compact, low cost and power-efficient devices connected with each other to perform monitoring and computational tasks. Enabled by recent advances in micro-electromechanical systems (MEMS) [3,4] and wireless communication technologies, tiny, cheap, and smart sensors have been developed providing unprecedented opportunities for a variety of civilian and military applications. Prolonged network lifetime, scalability, node mobility and load balancing are important requirements for any WSN. Sensor nodes in WSN rely on battery power for its energy requirements. But battery is limited source of energy. Replacing battery sources frequently is not a good option as it is practically not feasible. Use of large batteries with high capacities makes sensor nodes bulky.

2. PROBLEM IDENTIFICATION

A wireless sensor network (WSN) is network of sensor nodes with limited energy. Energy consumed energy during communication is affected exponentially by the distance between the communicating nodes. Performance of WSN depends on its energy consumption and determines its network lifetime. Therefore, managing energy consumption is a vital task in WSN performance. Clustering the sensor nodes is an effective technique to achieve these goals.

Initially, Direct Transmission (DT) and Minimum Transmission Energy (MTE) were two classical approaches proposed [5] for lifetime of WSNs. In DT, sensors transmit its sensed data directly to the Base Station (BS). This resulted the sensor nodes far away from the Base Station (BS) to die first. On the other hand in MTE, sensors near the BS would die first because they act as relays for sensors that are far from the BS. Though simple and easy to implement these classical approaches did not guarantee balanced energy utilization in the network Therefore, designing energy-aware clustering protocols became an important factor for extending the lifetime of sensors.

Clustering can be viewed as optimization problem with respect to formation of clusters and selection of cluster heads. Clustering is a non-deterministic problem due to varying number of nodes, their random location in search space and non-predictable of communicating nodes.

There are plethora of WSN routing protocols that minimize energy used, extending WSN life subsequently [6- 14]. Clustering can also improve data aggregation mechanisms, reduce the workload of each sensor to save energy and thus increase the overall lifetime of the system [15]. WSN routing must be optimized with respect to selection of cluster Heads and formation of clusters. Many greedy algorithms have been proposed to choose cluster heads based on the criteria such as (i) lowest-ID clustering algorithm, (ii) highest-connectivity clustering algorithm, (iii) least clustering change algorithm and (iv)weighted clustering algorithm. Similarly many clustering algorithms were proposed such as Linked cluster algorithm, Energy-efficient adaptive clustering, Energy-efficient distributed clustering, etc [16]. But there is need for maximize efficient utilization of energy of sensor nodes for increased network lifetime. But need of an optimized energy utilization clustering algorithm is desirable with increasing sizes of WSNs.

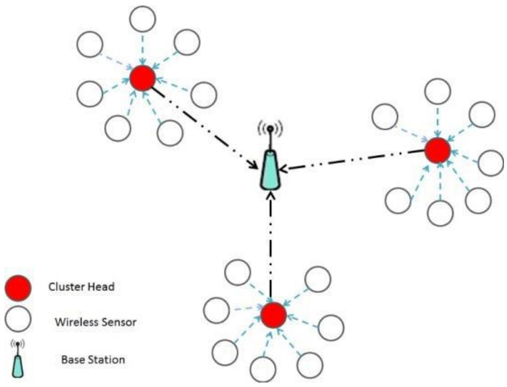

Figure 1 Process of clustering in WSNs

An optimization problem is generally recognized to be nondeterministic as well as fuzzy in nature. Evolutionary algorithms (EAs) have ability to identify global minima in the search space and use constrained programming technique to transform the stochastic problem into its deterministic form.

3. EVOLUTIONARY ALGORITHMS FOR OPTIMIZATION PROBLEMS

Nature has inspired many algorithms for optimization of NP hard problems. A principle behind nature inspired algorithms is efficiency, interpreted as survival of fittest theory in living beings.

This can be relying on Genetic algorithms which are based on survival of fittest theory by replicating best fit individuals in a population or based on foraging behavior of animals to get energy in least time known as foraging. Genetic Algorithm (GA) [17] and Simulated Annealing (SA) [18] are commonly used EAs. In the early 1970s, Genetic algorithm was developed by John Holland, which inspired by biological evolution such as reproduction, mutation, crossover and selection. Simulated annealing (SA) was developed from inspiration by annealing in metallurgy, a technique involving heating and cooling of a material to increase the size of its crystals and reduce their defects. Swarm Intelligence (SI) is another class of Evolutionary algorithms which are gaining significance in optimization problems. This class of [19],[20] meta-heuristic algorithms include Particle Swarm Optimization (PSO) [21]-[22], Ant Colony Optimization (ACO) [23], Artificial Bee Colony algorithm (ABC) [24-26], Glowworm Swarm Optimization (GSO) [27], Bacterial Foraging Optimization (BFO) [28], Cuckoo Search [29], Firefly Algorithm (FA) [30-31] , Bat Algorithm (BA) [32] and flower pollination algorithm[33].

Of these all proposed EAs significant research has been pursued using some while others are still evolving to achieve comparable performance. The popular EAs used for clustering and proven to show distinct improvement have been discussed below:

Genetic Algorithms (GAs): Using GAs, the problem is encoded into population of chromosomes[34] where each chromosome represents possible solutions. A fitness function is defined taking into account all the parameters which need to be optimized. Fitness function is evaluated to estimate the quality of each individual in the population. The individuals in a population undergo crossover and mutation to produce offsprings. Best fit individuals are replicated using crossover which makes new solution by concatenating parts of two selected chromosomes. Mutation introduces diversity and ensures solutions are not trapped in local minima. Number of iterations is run, to reach optimized solution. GAs support massive parallelism and give solution at every stage of optimization process. LEACH [35] protocol proposed by Heinzelman et al was an effective solution to power constraint problem of WSNs as it formed clusters in a self organized manner. Rather it is the first dynamic cluster head protocol for WSN using homogenous stationary sensor nodes. LEACH is suited for applications involving constant monitoring and periodic data reporting. LEACH protocol runs in many rounds. Each round contains two phases: cluster setup phase and steady phase. In cluster setup phase, it performs organization of cluster and selection of cluster head. Cluster head node is much more energy sensitive than being a non-cluster node. Thus, LEACH incorporates randomized rotation of the high-energy cluster head among the sensors.

Many variants of LEACH have been explored over the time [7-10, 12-14]. But LEACH- GA variants have been sufficiently explored to achieve efficient energy utilization based clustering in WSNs. Zhang et al [36] conducted in-depth study of LEACH protocol and based on its shortcomings and proposed LEACH-SAGA protocol. In this protocol, simulated annealing and genetic algorithm are used for clustering considering the residual energy of the nodes and the average energy of the cluster. Liu and Ravishankar [8] proposed GA-LEACH for clustering in heterogenous WSNs. [5] Mohammed et al presented a new Genetic Algorithm-based Energy-Efficient adaptive clustering hierarchy Protocol (GAEEP) to efficiently maximize the lifetime and to improve the stability period of Wireless Sensor Networks. [37] Sheta and Solaiman proposed a hybrid K-means PSO/GAs clustering algorithm. Both the KPSO and KGAs is used to define the sensors belonging to each cluster and the best CHs. KPSO and KGAs were separately applied to select cluster heads from clusters obtained by K-means clustering algorithm.

Sharma et al [38] proposed GA algorithm based on LEACH protocol. The proposed algorithm begins by randomly selecting cluster-heads, which are then optimized based on fitness function. Depending on number of nodes and their locations, the proposed algorithm is able to find an appropriate number of cluster-heads and their locations. The proposed algorithm takes parameters both energy of node and its distance from BS as criteria in fitness function. As proved by simulation results, the proposed algorithm has prolonged network lifetime by increasing the number of rounds at which half the number of nodes die and the number of round at which last node dies inside the network. Also number of packets transmitted as increased by factor of 10 when compared to that in LEACH.

[39] Halgamuge et al propsed use of Genetic Algorithms for energy optimization and cluster fitting for fully wireless and hybrid sensor networks. It was also suggested that dynamic clustering methods can be extended using the GA based methods. Battery lifetime of sensors can was anticipated to be part of objective function.

Particle Swarm Optimization: Particle Swarm Optimization (PSO) was developed in 1995 by Kennedy and Eberhart based on the social behavior of bird flock or fish school[21].

PSO was applied to obtain the optimum cluster layout using various fitness functions [40-44]. Different velocity models were suggested for PSO in [40-41] while different fitness functions were used in [42-44] PSO was also embedded in another algorithm to solve the WSN clustering problem as in [45]. Although it produces promising results, developing a low computational and high performance clustering algorithm is still a challenge.

Sheta and Solaiman[37] proposed a hybrid K-means PSO/GAs clustering algorithm. Both the KPSO and KGAs is used to define the sensors belonging to each cluster and the best CHs. KPSO and KGAs were separately applied to select cluster heads from clusters obtained by K-means clustering algorithm. Simulation results showed better results for KPSO with respect to the number of transmissions compared to the KGA proposed algorithm in terms of longer network lifetime. KPSO outperformed KGA by nearly 11 %.

Jing et al [44] proposed a non-uniform clustering mechanism using PSO algorithm. It strives to identify the right division of layers for non-uniform grid clustering and helps to optimize the energy consumption of the entire sensor networks. In addition, fitness is a multi-objective function based on different parameters.

Ma et al [46] proposed presented and analyzed an Efficient Node Partition Clustering protocol using Niching Particle Swarm Optimization (ENPC-NPSO), a protocol that partitions the network field efficiently. Further, selection of cluster heads considers the state of the network . This results in marked improvement in performance in terms of system lifetime and data delivery due to even distribution of energy dissipation. They even extended niching concept to identify adaptive heads in large sized clusters if needed depending both on average energy and distance of nodes in the cluster.

Bacterial Foraging Optimization: Inspired by E.Coli foraging strategy, Passino proposed Bacterial Foraging Optimization algorithm (BFOA) for optimization. Some successful foragers are bacteria like E.Coli, which uses chemical sensing organs to detect concentration of nutritive or noxious substances in environment to which it moves through tumbles and runs, avoiding noxious substances and getting closer to food areas in a process called 'chemotaxis'. The bacterium also secretes a chemical agent to attract peers, resulting in indirect communication.

Bhagawat et al [47] proposed LEACH-BFO algorithm for clustering of WSNs. It proposed to choose clusters using LEACH. Later each node finds its optimal cluster head by calculating fitness function using BFOA. It was found that new algorithm serves to be as betterment on the basic LEACH protocol. Simulation results showed higher performance of B-LEACH as compared to original LEACH, in terms of performance metrics like number of alive nodes, data transmission rate and energy dissipation within the network.

Sharma and Thakur[48] proposed an energy efficient algorithm for clustering in WSNs based on BFO, LEACH and HEED. The algorithm is proposed in three phases. Though no resulst were simulated but it expected to prolong network lifetime by efficient clustering.

Hongwei et al[49] proposed Cooperative Bacterial Foraging Optimization (CBFO)[49], to improve optimization of the original BFO for clustering problems. A novel clustering method was proposed and results showed a significant performance improvement in terms of accuracy, spped and robustness over BFO and PSO. The fitness optimization attained by conventional BFO and PSO in nearly 1000 iterations was achieved using CBFO in only 400 iterations.

Ant Colony /Artificial Bee Colony Optimization: Ant Colony Optimization was introduced by Dorigo and simulates the food searching strategy used by ants and Food foraging behaviour of honey bee colonies motivated Artificial bee colony algorithm. Using Ant Bee Colony (ABC) algorithm initialization of feasible solution is impossible in some cases and also scout bee made its search in random which at times may lead to an infeasible solution. So in order to overcome this problem Yuvraj and Krishnamoorthi proposed a hybrid of ABC BFO. The H-ABFO algorithm is done by replacing the Scout bee phase of ABC algorithm with BFO. Results were compared with traditional k-means algorithm. The proposed algorithm was tested by using real time datasets such as zoo, wine and the result obtained shows that the Intra Cluster Distance and Distance Index obtained is better than other Existing Swarm intelligence algorithm like ABC and BFO and for other Cluster Validity measures, the values are close enough to the Compared algorithms.

CONCLUSION

Evolutionary Algorithms begin with a population of solutions, which are changed through random selection and optimization of these solutions, guided by fitness function or the objective function. Since Evolutionary algorithms work on populations of individuals instead of single solutions, the search is performed in a parallel. Fitness function is very critical to performance of any evolutionary algorithm. It determines the criteria for optimization The way, the system differs depends on the generation of new solutions, random selection procedure and candidate solution encoding technique.

Advantages of using EAs over traditional optimization methods are listed below:

- Evolutionary algorithms search a population of points in parallel making the search faster.
- Evolutionary algorithms do not depend on derivative information but is determined by objective function and its value directs the search.
- Evolutionary algorithms are based on stochastic search not based on deterministic rules. So they are best suited for NP- hard problems.
- Evolutionary algorithms are a continuous optimization process and help identify the optimal solution if not best as stopping criteria is user-defined.
- EAs have ability to solve multi-objective optimization problems.

In recent years Swarm Intelligence based evolutionary algorithms have been proposed as an effective technique for solving complex optimization problems. Of all swarm based algorithms proposed Genetic Algorithms, Particle Swarm Algorithm (PSO) and Bacterial Foraging Optimization (BFO) have achieved significant improvements with respect to clustering in wireless sensor networks. More energy efficient clustering protocol could be proposed by exploring hybrid evolutionary algorithms for clustering, where dynamics of network such as more communication intensive routes, average time duration could be considered along with energy and distance parameters in objective function to be optimized.

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