GA-based approaches for Optimization energy and coverage in wireless sensor network:

State of the art

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Abstract. Wireless sensor networks (WSNs) have become one of the leading research subjects in computer science over the last few years. WSNs are resource-constrained concerning available energy, bandwidth, processing power, and memory space. Thus, optimization is essential to get the best results of these constraining parameters. Due to the advantages of genetic algorithms, different GA methods have been implemented to optimize different objectives like energy, coverage, QoS, and many other metrics. This paper presents a survey on the current state of the art during the last four years in wireless sensor network optimization using genetic algorithms to optimize energy consumption and the coverage of WSNs to give an up-to-date background to researchers in this field. Also, a classification of the works, based on the used methods, is provided.

Keywords: Optimization, genetic algorithm, wireless sensor network, energy, coverage.

1 Introduction

Sensor networks are tiny sensor nodes having elements created for specific operations like sensing the environment, processing data, and changing information with other nodes. When many sensor nodes are used to sense their material environmental conditions, they create a sensor network consisting of a sink node and sensor nodes which can be started from a few hundred to thousands in number[1][2]. WSNs have attracted significant attention recently from different research groups, and through their use, several applications are developed in the current and coming system[3]. WSNs are designed for various domains like monitoring events, agriculture, health care, and surveillance, which are classified into military, commercial, and medical applications[4]. In consideration of the application scenarios, WSNs may depend on crucial performance metrics to be optimized, like the energy consumption and network lifetime, because sensor nodes are powered by batteries, whose changing them is usually challenging and impossible. Moreover, the network coverage, latency, and many other metrics are critical for the quality of WSNs efficiency[5][6]. The aforementioned metrics often conflict with each other, thus balancing the trade-offs between them is very important in the matter of obtaining the optimal performance of real applications in WSNs. Consequently, multi-objective optimization (MOO) can be used for solving the previous problem[7]. MOO has been an essential topic of interest to researchers for solving various multi-objective optimization problems, in which many objectives are treated concurrently subjected to a set of limitations[7]. Nevertheless, it is unattainable for multiple objectives to reach their particular optima simultaneously. Therefore, there may not be a unique optimal solution, which is the most desirable regarding all objectives. However, a set of Pareto-optimal, which is named Pareto front (PF), could be obtained. In other words, the PF is formed by a particular set of solutions, for which none of the several objectives can be developed without sacrificing the other objectives[8]. In order to find the PSs of multi-objective problems, Various approaches have been proposed, such as nature-inspired, metaheuristics, and mathematical programming-based scalarization methods. Multi-objective problems are usually solved by bio-inspired approaches, such as swarm intelligence algorithms[9] and evolutionary algorithms[10]. Due to the advantage of genetic algorithms, they have been the most broadly used approach in the family of multi-objective evolutionary algorithms[11]. This paper provides a study on the current state of the art during the last four years in wireless sensor network optimization. This article examines the papers with GA-based methods to optimize energy consumption and the coverage of WSNs to give an up-to-date background to researchers in this field. Also, we classify these papers based on the type of the used GA methods to present a smooth overview and clear arrangement of ideas to readers.

1.1 Classification of GA-based Methods

Based on the methods used to optimize different objectives, Table 1 shows a classification of all the papers in this work upon the type of the method used (scheduling, energy-efficient, optimal path, clustering, mobility), and Table 2 shows the additional method used beside the GA and the optimization objectives (energy, coverage…) of each reference.

Table 1. Classification of GA-based methods.

ref	*scheduling*	*Optimal path*	*Clustering*	*Energy-efficient*	*Mobility*
12	X				
13	X				
14	X				

15	X				
16	X				
17	X			X	
18			X	X	
19				X	
20				X	
21				X	
22		X	X		
23		X			
24		X			
25		X			
26		X			
27		X			X
28			X		
29			X		
30			X		
31			X		
32		X	X		
33					X
34					X

Table 2. Classification based on optimization objectives.

Ref	Other used Method	Optimization Objectives
12	Maximum number of covers	Energy, Coverage
13	Maximum number of covers	Energy, Coverage
14	unsupervised learning	energy
15	K-coverage	Energy, Coverage
16	Kuhn-Munkres parallel GA	Energy, Coverage
17	3D protocols	Energy, Coverage, data delivery reliability
18		Energy

19		Energy
20	probabilistic sensor detection	Energy, Coverage
21		Energy, Coverage
22		Energy, Coverage
23		Energy
24	Fuzzy Algorithm, agent node selection	Energy
25	routing	Energy, data delivery reliability, Fault tolerance
26	Multiple sinks	Energy
27	adaptive balance function	Energy
28		Energy
29	Artificial bee colony	Energy, Coverage
30	Fuzzy algorithm	Energy, received data packets
31	Relay nodes	Energy
32	Cluster division region	Energy
33		Energy, Coverage, optimal movement of mobile sensor
34		Energy

1.2 Scheduling

Wireless sensor network lifespan for large-scale monitoring systems is represented as the period that all targets can be covered. One method to prolong the lifetime is to separate the deployed sensors into disjoint subsets of sensor covers so that all targets can be covered by every sensor cover and operate by turns (scheduling). Therefore, the high number of sensor covers that can be reached, the more prolonged sensor network lifetime can be achieved[12]. Obtaining the highest number of sensors covers can be done via conversion to the Disjoint Set Covers (DSC) problem, which has been determined to be NP-complete. For this, the existing heuristic algorithms either get inadequate solutions or take exponential time complexity. Thus, the authors in[13] propose a genetic algorithm to resolve the DSC problem by using a new parameter called the Difference factor (DF). In[14], an unsupervised learning method for topology control is offered to increase the lifetime of ultra-dense WSNs. Further, it schedules some members in the cluster to sleep to save the node energy utilizing geographically adaptive fidelity. For the purpose of achieving continuous coverage in tracking and monitoring applications, the target needs to be covered by more than one sensor concurrently. Mohamed Elhoseny et al. used a GA-based K-coverage approach to find the optimum sensor covers for K-coverage environments. Then a covers control method that shifts between several covers to enhance the network lifetime is implemented[15].

Because of the large-scale WSNs, current set cover algorithms cannot afford adequate performance for WSNs scheduling. The authors in[16] have developed a Kuhn-Munkres parallel genetic algorithm for the set cover problem and used it for the lifespan maximization of large-scale WSNs. They used the divide-and-conquer procedure of dimensionality reducing. Firstly, the target field is separated into various subareas, and then individuals are evolved separately in every subarea until the state factor arrives at a predefined value. The developed algorithm is then used to splice the solutions achieved in each subarea to generate the whole problem's global optimal solution. Otherwise, to enhance the global performance, another sensor schedule strategy is improved.

Even though the previous WSN approaches are created to be used on Two-Dimensional (2D) areas under models that rely on measuring the Euclidean distance between sensors, in reality, sensors are deployed in the 3D field in several applications. Thereby, Riham Elhabyan, Wei Shi, and Marc St-Hilaire[17] proposed a multi-objective method (NSGA-CCP-3D) to design an energy-efficient, scalable, reliable, and coverage-aware network configuration protocol for 3D WSNs. The principal purpose of the proposed approach is to find a simultaneous solution to conserve full connectivity and coverage in the 3D field by reaching the optimal status (cluster head, active, or inactive) for every sensor in the network.

1.3 Energy-efficient protocols:

The number and the position of cluster-heads are strictly affecting the whole energy consumption. Therefore, A Zahmatkesh et al.[18] introduced a multi-objective Genetic Algorithm to create energy-efficient clusters for wireless sensor networks. So, as the first objective is to create an optimal number of cluster heads and cluster members, the distance between sensor nodes for data transmission is considered as the second objective. Thus, the approach minimizes the nodes' energy consumption and the cost of transmission in the network.

Another approach based on a GA is introduced in[19] to find the optimal number of sensors in each cover set which are covering critical targets for a fixed duration (working time) to maximize the network lifetime of WSN. The authors formed the target coverage problem as a maximum network lifetime problem (MLP) and represented it by applying linear programming.

Jie Jia et al.[20] have proposed a new energy-efficient coverage control algorithm (ECCA) in wireless sensor networks. The object of ECCA is to activate only the required number of sensor nodes in a densely deployed environment. Two constraints control the algorithm: one is the specific coverage rate, and the other is the number of the selected nodes from the complete network. Likewise, it can avoid partial optimized solutions due to exploring the entire state-space. Although an accurate probabilistic sensor detection model is carried for a realistic approach, the ECCA algorithm can achieve balanced performance on various detection sensor models while preserving an excellent coverage rate. The authors have also explained how the model can be utilized in the coverage control scheme.

In contrast to the methods mentioned above, the GA approach in[21] aims to optimize the number of potential positions to provide sensor m-connected and target K-covered. Therefore, the method can reach an excellent trade-off between target coverage and energy consumption.

The authors in[22] aim to present an energy-efficient clustering protocol called Hybrid Weight-based Coverage Enhancing Protocol (WCEP) for area monitoring to prolong lifetime. The WCEP helps choose suitable cluster heads and their corresponding cluster members using the weighted sum approach to minimize the energy consumption while maintaining complete coverage and find optimal routing path by using a GA.

1.4 Optimal path:

Due to the impact of direct transmission on enhancing energy consumption when the Cluster head is far from the base station (BS), there has been increased interest to address this problem. The work proposed in [23] concentrates on developing an optimal multi-hop path between a source (CH) and a destination (BS), thereby decreasing energy consumption, which enhances the network lifetime compared with the direct transmission process. A genetic algorithm is used to achieve an optimal path by introducing a new fitness function. Moreover, changes in the CHs selection are introduced to improve the performance of the GA concerning the execution duration and the quality of the chromosomes. Instead of the arbitrary selection of cluster head in the previous work, the used method in [23] selects the CHs efficiently (via three levels) and introduces a new mechanism that can attain an optimal multi-hop path in WSNs. Furthermore, the proposed mechanism decreases the length of the chromosomes of GA and thus the execution time is decreased, by contrast to conventional GA.

Authors in[24] choose to work with a fuzzy logic mechanism using the distance from the base station, the trust value of the node, and energy consumption as parameters to select a particular agent node that collects data and transmits it to the base station. Moreover, in the second phase, they implemented the transmission and receiver energy consumption with a new fitness function in GA to prolong the network lifetime by finding the optimal multipath route. Among the significant factors to the sufficient overall network and application operation are energy consumption and data delivery. Therefore, a multi-objective integer problem (MOIP) is presented in [25] to obtain fitting solutions regarding such trad-off in routing problems using a Non-dominated Sorting Genetic Algorithm in the network with only one sink. On the other hand, the authors in [26] proposed a GA-based optimization routing path in WSNs but with the deployment of multiple sinks, where the nodes forward the packets towards the nearest sink.

In contrast to the previous static wireless sensor network, Shanthi et al. [27] introduced new progress in the Genetic algorithm and named it a Dominant Genetic

Algorithm to define the optimum energy-efficient route path connecting sensor nodes and also determine the optimal trajectory for the mobile node that gather data. Although the proposed method has been applied under two different scenarios, it proves that it has faster convergence and high reliability over the conventional GA in various experiments.

1.5 Clustering

Some of the significant factors that affect the network lifetime are the sink distance and the cluster distance. Nevertheless, the available work neglects the influence of the network's general consumption and network energy consumption balance on clustering. Hence, the authors of [28] created an extension model to LEACH protocol, the many-objective energy balance model of cluster head. They considered four objectives to determine the cluster head node: the sink node distance, cluster distance, the total energy consumption of the network, the network energy consumption balance. Meantime, A new approach is proposed (LEACH-ABF) based on adaptive balance function to resolve the model. ABF merges the diversity and convergence functions and uses genetic operations to produce a more desirable solution. Experiments prove that LEACH-ABF has a better balance of energy consumption and prolongs the lifetime of WSN compared to other existing approaches. Also, the approach in [29] used a genetic algorithm for selecting the cluster heads based on four parameters (residual energy, density, centrality, and distance). Additionally, the Artificial bee colony method is applied for selecting nodes in each cluster of the chosen CH.

Only two parameters are chosen [30] to develop a new protocol based on Fuzzy logic and genetic algorithm for WSNs. The fuzzy logic approach for selecting CHs relies on two principal factors: the distance between the node and the BS and node residual energy. The Genetic Algorithm is used as a fitness function for arranging the fuzzy rule table. As a result, cluster heads' selection becomes more effective, and the cluster forming gets more precise. Due to all the nodes nearly die simultaneously, the network lifetime of WSN is prolonged, and the number of data packets received in the sink is maximized. Another routing protocol [31] is an aggregate of Micro Genetic algorithm with LEACH protocol. The µGA-LEACH protocol gives strength to the cluster head (CH) selection and decreases the network's energy consumption using the relay nodes to make communication easier between CHs and BS at large distances.

In [32], the genetic algorithm-based clustering and Routing (LECR-GA) method was created to maximize the WSN lifetime and improve its quality of service by choosing the best of genetic algorithm operations, chromosome representation, and fitness function. Thus, the approach has reached higher system operability and enhance data rate with keeping satisfactory complexity and minimize the energy consumption of nodes by choosing the nearest CH with the appropriate parameters (more energy and less distance to achieve data).

1.6 Mobility:

The mobile wireless sensor cannot cover the whole target moving path due to its inadequate number and short sensing range. Thus, in [33], a new approach is proposed to obtain complete coverage for the moving target on a preselected trajectory with a restricted number of mobile sensors. Mobile sensors must change their previous position to a new position in the path to affording complete coverage. The authors minimized the total moving distance of mobile sensors. The farthest movement distance is minimized using a Genetic algorithm-based approach to save energy and prolong the network lifetime.

In [34], an optimizing algorithm for Connected Dominating Set based on anchor nodes was proposed. It used arbitrary mobility for the anchor and the unknown nodes. The optimization method uses the genetic algorithm with elitism procedure so that the fittest solution can be maintained for fast convergence of the global solution. So as the anchor nodes execute the necessary and significant computations in the proposed algorithm, the network lifetime increases.

2 Conclusion

In this paper, we have collected the most important articles concerned with addressing optimization in WSNs. Due to their advantage over the other optimization methods, we have chosen the GA-based approaches in this work. Also, we have limited the time range of the studied articles to the last four years to make the researchers understand the latest findings in this field. Additionally, we have provided a classification of the articles based on the utilized method type and we have afforded a table of each paper's Optimization Objectives. This work allows a better understanding of the proposed approaches during the last four years and is, consequently, a basis for future ideas and works.

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