Genetic Algorithm based Sleep Scheduling for Maximizing Lifetime of Wireless Sensor Networks

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ABSTRACT

In most of applications of Wireless Sensor Networks(WSNs), it is expected that a solution finding a number of non-disjoint cover sets will save more energy. Base on sleep scheduling method, this paper proposed a modified genetic algorithm to maximize the lifetime of networks and schedule the sensors in the sets successively. Results show that under the same conditions, the proposed algorithm can always find the sets with maximum lifetime and consume less computation time while comparing with the recently published algorithms.

CCS CONCEPTS

• **Theory of computation → Optimization with randomized search heuristics**; **Evolutionary algorithms**; *Scheduling algorithms*;

KEYWORDS

sleep scheduling, non-disjoint cover sets, genetic algorithm, wireless sensor networks

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1 INTRODUCTION

Since the sensor has the limited power, how to extend the lifetime of the sensor nodes is a critical issue of research in WSNs. As a main method to improve the energy efficiency, sleep scheduling is used in various research, such as disjoint cover sets problem. Cardei et al. [4] propose an algorithm to solve the problem using graphs, in [2] [7], approximation algorithms are proposed to extend the lifetime of WSNs. Besides, heuristic algorithms [1, 5, 8, 10--12] are preferred to compute the maximum number of covers.

However, many applications are designed as hybrid / heterogeneous sensors networks [9] [13] in which different sensors involved have different capability and energy supply. Hence the non-disjoint cover sets problem is more worth discussing. [3] first transfer the non-disjoint cover sets problem to Minimum Weight Sensor Cover Problem, then an approximation algorithm is proposed. The paper in [14] makes multiple layers in a cover set, when some sensors of former layer ran out of power, the sensors of latter layer will replace the sensors which are without energy. Then a modified Ant Colony Algorithm(MCACO) is proposed to maximize the network lifetime. And the paper in [6] designed a deterministic algorithm based on a linear programming model to achieve the optimum by classifying target points.

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2 PROPOSED ALGORITHM

For solving the non-disjoint cover sets problem, we propose a genetic algorithm with adaptive crossover and multiple mutation operators(ACMMGA). Given different remaining energy of each sensor, the algorithm can find the non-disjoint cover sets with maximum sum of the lifetime of the sets.

Firstly, the representation and initialization of chromosomes are introduced. There are a set of feature values g_j related to each gene, g_j indicates the scheduling number for activation. Each gene G_i in the chromosome is represented as

$$G_i = (g_{i1}, g_{i2}, ..., g_{ij}) \tag{1}$$

where g_{ij} is the scheduling number in ascending order, i is the gene number and corresponds sensor i. Then each chromosome C_h in the population is represented as

$$C_h = (G_{h1}, G_{h2}, ..., G_{hN}) \tag{2}$$

where N is the total number of the sensors deployed in the area, h is the chromosome number. In the step of initialization, all the sensors are in the same set, so that $C_h = ((1), (1), ..., (1))$.

Secondly, a fitness function for evaluation of chromosome is designed as follow.

$$F_h = w_1 L_h + w_2 P_{T_h+1} \tag{3}$$

where L_h is the total lifetime of chromosome C_h. P_{T_h+1} is the coverage percentage of the incomplete cover set $T_h + 1$. w_1 and w_2 are two weights for L_h and P_{T_h+1}. Then an adaptive crossover can have more probabilities to selecting genes from the parent with bigger fitness and produce new offspring.

To preserve the diversity of the population, there are four mutation operators should be executed after crossover. Respectively, **Evolutionary Mutation** is to schedule the coverage redundant sensor in the complete cover set to the incomplete cover set. **Growing Mutation** is to schedule the lifetime redundant sensor to the incomplete cover set. And to avoid the local optimum, **Retrograde Mutation** and **Critical Mutation** can transfer back the sensors of the last set to any other set or a critical set.

3 EXPERIMENT AND RESULTS

As a representative example, STHGA [8] method, MCACO [14] and EXACT [6] are used for comparison. MCACO and EXACT

Table 1: TEST RESULTS FOR DIFFERENT NUMBERS N OF SENSORS AND SENSING RANGE R

Cases				ACMMGA			STHGA			MCACO			EXACT	
NO.	N	R	$\widetilde{T}$	Mean	t(ms)	ok%	Mean	t(ms)	ok%	Mean	t(ms)	ok%	Result	t(ms)
1	100	4	6	**6**	19	100	**6**	54	100	**6**	**17**	100	**6**	124
2	100	6	21	**21**	74	100	**21**	438	100	**21**	**49**	100	**21**	93
3	100	8	25	**25**	**46**	100	**25**	213	100	**25**	57	100	**25**	80
4	100	10	38	**38**	**60**	100	**38**	399	100	**38**	81	100	**38**	100
5	150	8	53	**53**	171	100	**53**	1978	100	**53**	**150**	100	**53**	286
6	200	8	77	**77**	**712**	100	76.96	11808	97	**77**	726	100	**77**	1106
7	200	10	122	**122**	**1040**	100	121.69	50862	72	**122**	2904	100	**122**	1624

are heuristic and approximation algorithms for non-disjoint cover sets problem respectively. Besides, the STHGA is to find the maximum number of disjoint sets of sensors to maximize the lifetime of the network by using a modified genetic algorithm. And to ensure that the STHGA can be worked for solving the non-disjoint set problem, a preprocess for STHGA should be added. The preprocess is regarding a sensor with l unit lifetime as l sensors with 1 unit lifetime.

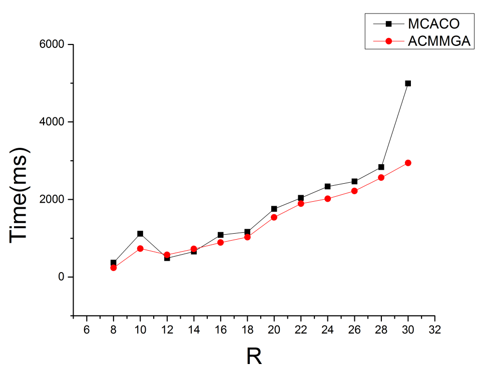

Figure 1: Comparison of the time used for obtaining the optimization results by ACMMGA and MCACO when R increases from 8 to 30 for the test case $L = 50, W = 50, N = 200$.

To test the efficiency of the proposed algorithm, different test cases are designed for area coverage problem and simulate a network with N sensors randomly located in a 20×20 area. In Table I, ACMMGA, STHGA and MCACO are executed 100 independent times on each case and use the average results of comparison. The number N of sensors and sensing rang R are variables, $\widetilde{T}$ is the maximum lifetime of cases, $ok\%$ is the successful percentage, $Mean$ is the mean result for each algorithm. Besides, a time limit is set for the execution of every algorithm, which is $60,000ms(10min)$. Once the execution of an algorithm has exceeded the time limit, it will stop and fail to find the optimal solutions.

From Table I, ACMMGA, MCACO and EXACT can always obtain the optimal solutions in all cases while the successful percentage of STHGA is 97% and 72% in case 6 and 7. By comparing the calculation time of four algorithms, ACMMGA and MCACO are much shorter than that of the others. In case 3, 4, 6, 7, ACMMGA is faster than MCACO. Then We further compare with the calculation time of ACMMGA and MCACO when sensing range R vary between 8 and 30 and $L = 50, W = 50, N = 200$. As the Fig.1 indicates, the ACMMGA runtime is much smaller than MCACO runtime with the increment of sensing range.

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