Extended Binary Particle Swarm Optimization Approach for Disjoint Set Covers Problem in Wireless Sensor Networks

Zhi-hui Zhan[1], Jun Zhang[1] (Corresponding Author)*, Ke-jing Du[2], and Jing Xiao[3]
[1]Department of Computer Science, Sun Yat-sen University, Guangzhou, P. R. China, 510275
[1]Key Laboratory of Digital Life, Ministry of Education, P. R. China
[1]Key Laboratory of Software Technology, Education Dept. of Guangdong Province, P. R. China
[2]Academy of Entrepreneurship, Sun Yat-sen University, Guangzhou, P. R. China, 510275
[3]School of computer science, South China Normal University, Guangzhou, P. R. China, 510631
*junzhang@ieee.org

***Abstract*—This paper proposes to use the binary particle swarm optimization (BPSO) approach to solve the disjoint set covers (DSC) problem in the wireless sensor networks (WSN). The DSC problem is to divide the sensor nodes into different disjoint sets and schedule them to work one by one in order to save energy while at the same time meets the surveillance requirement, e.g., the full coverage. The objective of DSC is to maximal the number of disjoint sets. As different disjoint sets form and work successively, only the sensors from the current set are responsible for monitoring the area, while nodes from other sets are sleeping to save energy. Therefore the DSC is a fundamental problem in the WSN and is significant for the network lifetime. In the literature, BPSO has been successfully applied to solve the optimal coverage problem (OCP) which is to find a subset of sensors with the minimal number of sensors to fully monitor the area. In this paper, we extend the BPSO approach to solve the DSC problem by solving the OCP again and again to find the disjoint subsets as many as possible. Once finding the minimal number of sensors for the OCP to fully monitor the area, we mark these sensors as unavailable and repeatedly find another subset of sensors in the remained WSN for the OCP. This way, BPSO can find disjoint subsets of the WSN as many as possible, which is the solution to the DSC problem. Simulations have been conducted to evaluate the performance of the proposed BPSO approach. The experimental results show that BPSO has very good performance in maximizing the disjoint sets number when compared with the traditional heuristic and the genetic algorithm approaches.**

Keywords- Wireless sensor networks (WSN), disjoint set covers (DSC), particle swarm optimization (PSO)

I. INTRODUCTION

Wireless sensor network (WSN) is a very new technology which has become one of the hottest and most challenging research areas recently [1]. The WSN consists of lots of sensor nodes that monitor the area for specialized applications such as battlefield surveillance, habitat monitoring, environmental observation, health applications, and many others [2]. The environments of these applications are usually not friendly and it is difficult to deploy the sensors determinately. Therefore, a large amount of nodes are randomly deployed in the area, resulting in more sensors than required. Current researches have found that optimally scheduling the sensor nodes and making the redundant nodes turned off to sleep can significantly save the energy to prolong the network lifetime [3].

In the literature, many researches transform the issue of saving energy for prolonging network lifetime to the optimal coverage problem (OCP) [4]. The OCP is based on the fact that the WSN contains a large number of sensor nodes. As a result, many nodes may share the same monitored regions, and some of the nodes are redundant and can be turned off to preserve the energy while the others still work to provide the full coverage. Activating only the necessary sensor nodes at any particular moment can save energy. Therefore, the OCP is a fundamental problem in WSN with the objective of finding out a minimal set of nodes to monitor the area, and turning off the other redundant nodes to save energy, while at the same time meeting the full coverage requirement. This way, not only the nodes can reduce the energy consumption caused by the nodes confliction or the neighborhood communication, but also the network lifetime can be significantly prolonged because the nodes can be scheduled to work in turn. In the literature, many approaches have been proposed to solve the OCP [3][4]. In Zhan *et al*.'s work [4], the authors formulated OCP as a 0/1 programming problem and designed evolutionary computation algorithms to efficiently solve the problem. As the binary particle swarm optimization (BPSO) approach proposed in [4] outperforms many existed approaches and a genetic algorithm (GA) in solving the OCP, we will further use the BPSO approach when extend OCP to the disjoint set covers (DSC) problem in this paper.

DSC is to divide the sensor nodes into different disjoint sets and schedule them to work one by one in order to save energy while at the same time meets the surveillance requirement, e.g., the full coverage. The objective of the DSC is to maximal the number of disjoint sets. Even though minimizing the work nodes (i.e., solving the OCP) can prolong the network lifetime, it is more interesting to investigate the division of the nodes (i.e., solving the DSC problem) because the later one is more intuitive for prolong the network lifetime. In the literature, some approaches such as those in [5], [6], and [7] focused on dividing the original deployed sensor nodes into disjoint sets as many as possible and schedule the sets to work in turn. It should be noticed that the approach in [5] can guarantee the full coverage while the ones in [6] and [7] can not. In this paper, we extend the BPSO approach in [4] which is for solving the OCP to solve

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the DSC problem. The BPSO approach for the DSC problem is to solve the OCP again and again to find the disjoint subsets as many as possible. Therefore, in this paper, the DSC problem is not directly defined, but is defined based on the OCP. Once the OCP is solved by BPSO [4], that is, have found the minimal number of sensors to fully monitor the area, we can regard these sensors being a subset cover. Then, we mark these sensors as unavailable and repeatedly find another subset of sensors in the remained WSN for the OCP. This way, BPSO can find disjoint subsets of the WSN as many as possible, which is the solution to the DSC problem.

Simulations are conducted to evaluate the performance of the BPSO approach in solving the DSC problem by repeatedly solving the OCPs. Moreover, the GA which was proposed in [4] to solve the OCP is also extended in this paper to solve the DSC problem and is compared with BPSO. The state-of-the-art approach proposed in [5] is also adopted in the comparisons because it can provide full coverage. Experimental results show that the BPSO approach wins both the GA and some state-off-the-art approaches in maximizing the disjoint sets number of WSN in different network environment.

The rest of this paper is organized as follows. Section II gives the problem formulations of the OCP and DSC in WSN. Then Section III proposes the methodology that uses the BPSO approach to solve the DSC problem. Section IV gives the experimental results and comparisons. At last, conclusions are summarized in Section V.

II. OCP AND DSC

A. OCP

The problem definition for the OCP can be referred to [4], and is briefly described as follows. Given an $L\times W$ (Length×Width) rectangle area A for monitoring, and an amount of N sensors are randomly deployed in the area. The OCP is to determine using only a sub-set of M sensors from the N sensors to fully cover the monitored area, supposed that the area can be fully covered by the original N sensors (as the N sensors are randomly deployed, the area may be not fully covered in the original network topology, we do not consider this situation in our paper). The objective of the OCP is to minimize the number of M. In order to know whether the area A is fully covered by the sensors network, we assume that the location of the sensor is prior known. Moreover, the area is divided into grids and the coverage issue can be transformed to check whether each of the grids is covered by at least one active sensor.

All the N sensors form the sensors set $S=\{s_1, s_2, \dots, s_N\}$, where each sensor node s_i is with the location (x_i, y_i) and the sensor radius R. For any grid $g=(x, y)\in A$ in the monitored area, the relationship between the s_i and the g is defined as:

$$P(s_i,g)=\begin{cases}1, & \text{if } (x-x_i)^2+(y-y_i)^2\le R^2\\ 0, & \text{otherwise}\end{cases} \tag{1}$$

where 1 means that the grid g is covered by the sensor s_i while 0 means the sensor s_i does not cover the grid g. Therefore, for any grid point g, if there exists at least one sensor $s_i(1\le i\le N)$ that makes $P(s_i,g)=1$ follow, we say that the g is covered by the sensor network. In this sense, the monitored area A is fully covered if any grid point g in the area is covered by the sensor network.

In the OCP, the area is monitored by an optimally selection sub-set $S^*=\{s_i, \mid s_i \text{ is selected}, 1\le i\le N\}$ with M sensors from the N sensors, with the constraint that the area A is still fully covered by the M sensors, and with the objective of minimizing the value of M, as:

$$\begin{aligned} &f=\min M, \quad \text{where } M=\left|S^*\right|, \quad S^*\subseteq S\\ &\textit{subject to} \quad (\oplus_{s_i\in S^*} P(s_i,g))=1, \quad \forall g\in A \end{aligned} \tag{2}$$

Here, the operator $\oplus$ results in a value of 0 if all the elements are 0. Otherwise, the result is 1 if at least one of the elements is 1.

B. DSC

The DSC problem is defined as:

$$\begin{aligned} &F=\max\ K\\ &\textit{subject to} \quad \text{(i) } \cup_{i=1}^{K} S_i\subseteq S\\ &\qquad \text{(ii) } S_i\cap S_j=\Phi, \quad \forall i\ne j\\ &\qquad \text{(iii) } (\oplus_{s_j\in S_i} P(s_j,g))=1, \quad \forall g\in A \end{aligned} \tag{3}$$

Here, the K is the number of DSC, the (i) constraint means that the unitization of all the sub-sets S_i must belongs to the original set S. The (ii) indicates that there is no intersection between any two different sub-sets S_i and S_j. The operator $\oplus$ in (iii) results in a value of 0 if all the elements are 0. Otherwise, the result is 1 if at least one of the elements is 1. Therefore this constraint guarantees that each sub-set S_i can fully cover the monitored area.

In this paper, the DSC problem is based on the OCP. The OCP model is very suitable for extending to the DSC problems in the WSN. This is because that minimizing the number of the active sensor nodes has a direct impact on the number of the disjoint sets. Finding a solution to DSC is to repeatedly find optimal solution to OCP. The first solution to OCP is the first sub-set cover in DSC. Then the sensors in this sub-set cover are marked as unavailable and the rest sensor nodes form a new WSN. By solving the OCP again and again, we can obtain the second, the third, the fourth sub-set cover in DSC, and so on. This way, the DSC problem can be solved.

III. METHODOLOGY: BPSO FOR DSC

By using the BPSO approach to solve the OCP, the DSC problem can be solved by the BPSO approach as Fig. 1.

Given a WSN with a set of sensors, the approach firstly checks whether the sensors can fully cover the monitor area. If not, the process reports a fail result K=0 and terminates. During the process, the algorithm repeatedly uses BPSO approach to minimize the number of active sensor nodes for the OCP [4]. These active nodes form the first sub-set. Then these nodes are marked as unavailable and the rest sensor nodes form another network topology. The BPSO approach is performed on the new topology to minimize the number of active sensor nodes, forming the second sub-set. The similar process goes on until the last network topology can not provide a full coverage for the area. In this sense, the number of maximal disjoint sets can be determined.

It should be noticed that this is a general extend technique that can also be used in other approach. For example, it is easy to extend the GA approach to solve the DSC problem by replacing BPSO to GA in the Fig. 1.

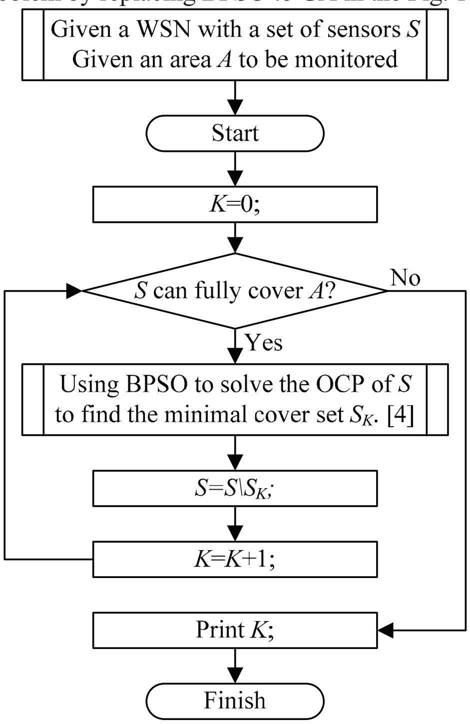

Figure 1. The flowchart of using BPSO to solve DSC.

IV. Experiments and Comparisons

The BPSO approach for solving the DSC problem is implemented and evaluated. The parameters configurations are the same as the ones in [4] used for solving the OCP. Refer to Section III, the core of using BPSO to solve the DSC problem is to use BPSO to solve OCP. Therefore, the parameters in [4] are directly used herein. Moreover, the GA parameters are the same as the ones proposed in [4].

Even though the work in [5], [6], and [7] addresses the maximization disjoint sets problem, but only the approach used in [5] can guarantee the full coverage. Therefore, we compare our approaches and the one of [5] in dealing with the maximization disjoint sets problem.

We adopt the same simulation environment as in [5] where the monitored area is a 500m×500m square. Different number of sensor nodes and different sensing ranges are tested, as shown in Table I. For each combination configuration of the sensor nodes N and the sensing range R in Table I, we randomly generate 3 network topologies and run the approaches 3 independent times for each topology. The mean results are calculated and compared with the upper bound of the disjoint sets number for each topology, as shown in Table II and Table III for the GA approach and the BPSO approach respectively.

TABLE I. The Simulation Environment

Environment	Sensor nodes N	Sensing range R
E1	100	200
E2	120	200
E3	150	200
E4	180	150
E5	300	80
E6	400	80

TABLE II. Results of GA in Solving the DSC Problem

Envir	Cases	Run1	Run2	Run3	Mean	UP	Run-Mean	UP-Mean	Accuracy
E1	Case1	10	10	10	10	11	10.22	11.67	87.62%
	Case2	11	10	10	10.33	12			
	Case3	10	11	10	10.33	12			
E2	Case1	13	13	10	12	15	9.33	12.00	77.78%
	Case2	10	7	8	8.33	11			
	Case3	7	8	8	7.67	10			
E3	Case1	13	10	13	12	16	10.44	14.33	72.87%
	Case2	12	10	10	10.67	15			
	Case3	9	10	7	8.67	12			
E4	Case1	8	5	6	6.33	9	7.33	9.67	75.86%
	Case2	7	7	**8**	7.33	8			
	Case3	8	8	9	8.33	12			
E5	Case1	**3**	2	2	2.33	3	1.89	3.00	62.96%
	Case2	1	1	1	1	3			
	Case3	2	**3**	2	2.33	3			
E6	Case1	3	**4**	3	3.33	4	3.22	4.33	74.36%
	Case2	3	3	**4**	3.33	4			
	Case3	2	4	3	3	5			

TABLE III. Results of BPSO in Solving the DSC Problem

Envir.	Cases	Run1	Run2	Run3	Mean	UP	Run-Mean	UP-Mean	Accuracy
E1	Case1	10	**11**	**11**	10.67	11	11.22	11.67	96.19%
	Case2	11	**12**	11	11.33	12			
	Case3	**12**	11	**12**	11.67	12			
E2	Case1	**15**	**15**	14	14.67	15	11.89	12.00	99.07%
	Case2	**11**	**11**	**11**	11.00	11			
	Case3	**10**	**10**	**10**	10.00	10			
E3	Case1	15	15	15	15.00	16	13.78	14.33	96.12%
	Case2	**15**	**15**	14	14.67	15			
	Case3	**12**	11	**12**	11.67	12			
E4	Case1	**9**	**9**	8	8.67	9	9.44	9.67	97.70%
	Case2	**8**	**8**	**8**	8.00	8			
	Case3	11	**12**	**12**	11.67	12			
E5	Case1	**3**	2	**3**	2.67	3	2.78	3.00	92.59%
	Case2	**3**	**3**	**3**	3.00	3			
	Case3	2	**3**	**3**	2.67	3			
E6	Case1	**4**	**4**	**4**	4.00	4	4.33	4.33	100.00%
	Case2	**4**	**4**	**4**	4.00	4			
	Case3	**5**	**5**	**5**	5.00	5			

The upper bound of disjoint sets number for each topology can be determined as follows. As the area has been divided into grids, for each grid, we can find out the number of sensors that cover it. Compare all these numbers and the minimal one is the upper bound of the disjoint sets number for this network topology. This method is also always used to study the *k*-cover of the WSN. The *k*-cover of the WSN tells that every point of the monitored area is covered by at least *k* different sensor nodes. Therefore, the nodes can be at most divided into *k* disjoint sets with the constraint that each set can fully cover the whole area. In this sense, the value *k* can be the upper bound number of the disjoint sets for this network topology. However, the *k* is a rough number and the true optimal number may be smaller than *k*.

The data presented in Table II and Table III shows that BPSO generally outperforms GA in solving the DSC problem. In most of the test cases, the BPSO approach can obtain the upper bound number of disjoint sets and the accuracy (denote by the quotient of Mean/UP) can reach higher than 96% in all the test environments.

We also compare the results obtained by the simulated annealing (SA) approach and the heuristic approach [5] in Table IV. The results show that both the GA and BPSO approaches outperform the SA approach. When compare the performance of the heuristic approach in [5] with GA and BPSO, the GA outperforms the heuristic on environment 1 and environment 4, while the BPSO outperforms the heuristic on environments 1, 2, and 4. This demonstrates that BPSO is more promising in solve the DSC problem to maximize the disjoint sets number of WSN.

TABLE IV. COMPARISONS OF DIFFERENT APPROACHES IN SOLVING THE DSC PROBLEM

Environment	SA [5]	Heuristic [5]	GA	BPSO
E1: 100-200	6.8	9.7	10.22	**11.22**
E2: 120-200	7	11.5	9.33	**11.89**
E3: 150-200	10.5	**18.5**	10.44	13.78
E4: 180-150	2.9	6.6	7.33	**9.44**
E5: 300-80	2.6	**4.3**	1.89	2.78
E6: 400-80	3.2	**4.5**	3.22	4.33

V. CONCLUSION

The BPSO approach has been extended to solve the DSC problem in WSN in this paper. We do not directly model the DSC problem in this paper but to solve it by repeatedly solving the OCP problem. We have described the implementation of using the BPSO approach to solve the problem. The performance is evaluated and compared with the state-of-the-art approaches and the GA approach. The experimental results have shown the effectiveness and efficiency of the proposed BPSO approach.

In the future work, we will try to use the most recent adaptive strategy [8], orthogonal learning strategy [9], machine learning technique [10], set-based method [11], aging leader strategy [12], and co-evolutionary technique [13] in to BPSO to design more efficient algorithm for solving the DSC problem in WSN. Moreover, other evolutionary computation algorithms like clustering-based adaptive GA [14], ant colony optimization [15][16], differential evolution [17][18], estimation of distribution algorithm [19], and brain storm optimization [20] are also promising to be applied to solve DSC, and more comparisons will be conducted by comparing with some recent algorithms [21][22][23].

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REFERENCES

[1] I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, “Wireless sensor networks: a survey,” *Computer Networks*, vol. 38, no. 4, pp. 393-422, March, 2002.

[2] M. Kuorilehto, M. Hannikainen, and T. D. Hamalainen, “A survey of application distribution in wireless sensor networks,” *EURASIP Journal on Wireless Communications and Networking*, vol. 5, pp. 774–788, 2005.

[3] C. F. Huang and Y. C. Tseng, “A survey of solutions to the coverage problems in wireless sensor networks,” *Journal of Internet Technology*, vol. 6, no. 1, pp. 1-8, 2005.

[4] Z. H. Zhan, J. Zhang, and Z. Fan, “Solving the optimal coverage problem in wireless sensor networks using evolutionary computation algorithms,” in *Proc. 8th Simulated Evolution and Learning, SEAL2010*, LNCS 6457, pp. 166–176, 2010.

[5] S. Slijepcevic and M. Potkonjak, “Power efficient organization of wireless sensor networks,” In *IEEE Int. Conf. on Communications (ICC)*, 2001, pp. 472–476.

[6] M. Cardei, D. MacCallum, X. Cheng, M. Min, X. Jia, D. Li, and D.-Z. Du, “Wireless sensor networks with energy efficient organization,” *Journal of Interconnection Networks*, vol. 3, no. 3-4, pp 213-229, Dec. 2002.

[7] C. Liu, K. Wu, Y. Xiao, and B. Sun, “Random coverage with guaranteed connectivity: joint scheduling for wireless sensor networks,” *IEEE Trans. Parallel and Distributed Systems*, vol. 17, no. 6, pp. 562-575, Jun., 2006.

[8] Z. H. Zhan, J. Zhang, Y. Li, and S. H. Chung, “Adaptive particle swarm optimization,” *IEEE Trans. Syst., Man, and Cybern. B*, vol. 39, no. 6, pp. 1362-1381, Dec. 2009.

[9] Z. H. Zhan, J. Zhang, Y. Li, and Y. H. Shi, “Orthogonal learning particle swarm optimization,” *IEEE Trans. Evol. Comput.*, vol. 15, no. 6, pp. 832-847, Dec. 2011.

[10] J. Zhang, Z. H. Zhan, Y. Lin, N. Chen, Y. J. Gong, J. H. Zhong, H. Chung, Y. Li, and Y. H. Shi, “Evolutionary computation meets machine learning: A survey,” *IEEE Comput. Intell. Mag.*, vol. 6, no. 4, pp. 68-75, Nov. 2011.

[11] W. N. Chen, J. Zhang, H. Chung, W. L. Zhong, W. G. Wu, and Y. H. Shi, “A novel set-based particle swarm optimization method for discrete optimization problems,” *IEEE Trans. Evol. Comput.*, vol. 14, no. 2, pp. 278-300, April 2010.

[12] W. N. Chen, J. Zhang, Y. Lin, N. Chen, Z. H. Zhan, H. Chang, Y. Li, and Y. H. Shi, “Particle swarm optimization with an aging leader and challengers,” *IEEE Trans. Evol. Comput.*, in press, 2012.

[13] Z. H. Zhan, J. Li, J. Cao, J. Zhang, H. Chung, and Y. H. Shi , “Multiple populations for multiple objectives: A co-evolutionary technique for solving multi-objective optimization problems,” *IEEE Trans. Syst., Man, and Cybern. B*, in press, 2012.

[14] J. Zhang, H. Chung, and W. L. Lo, "Clustering-based adaptive crossover and mutation probabilities for genetic algorithms," *IEEE Trans. Evol. Comput.*, vol. 11, no. 3, pp. 326-335, Jun. 2007.

[15] W. N. Chen and J. Zhang, "Ant colony optimization approach to grid workflow scheduling problem with various QoS requirements," *IEEE Trans. Syst., Man, and Cybern. C*., vol. 31, no. 1, pp. 29-43, Jan. 2009.

[16] Z. H. Zhan, J. Zhang, Y. Li, O. Liu, S. K. Kwok, W. H. Ip, and O. Kaynak, "An efficient ant colony system based on receding horizon control for the aircraft arrival sequencing and scheduling problem," *IEEE Trans. Intell. Transp. Syst.*, vol. 11, no. 2, pp. 399-412, Jun. 2010.

[17] Z. H. Zhan and J. Zhang, "Self-adaptive differential evolution based on PSO learning strategy," in *Proc. Genetic Evol. Comput. Conf.*, Jul. 2010, pp. 39-46.

[18] Z. H. Zhan and J. Zhang, "Co-evolutionary differential evolution with dynamic population size and adaptive migration strategy," in *Proc. Genetic Evol. Comput. Conf.*, Jul., 2011, pp. 211-212.

[19] J. H. Zhong, J. Zhang, and Z. Fan, "MP-EDA: A robust estimation of distribution algorithm with multiple probabilistic models for global continuous optimization," *SEAL 2010, LNCS 6457*, pp. 85-94, 2010.

[20] Z. H. Zhan, J. Zhang, Y. H. Shi, and H. L. Liu, "A modified brain storm optimization," in *Proc. IEEE World Congr. Comput. Intell.*, 2012, pp. 1-8.

[21] C. C. Lai, C. K. Ting, and R. S. Ko, "An effective genetic algorithm to improve wireless sensor network lifetime for large-scale surveillance applications," in *Proc. IEEE Congr. Evol. Comput.*, 2007, pp. 3531-3538.

[22] C. K. Ting and C. C. Liao, "A memetic algorithm for extending wireless sensor network lifetime," *Inf. Sci.*, vol. 180, no. 24, pp. 4818-4833, 2010.

[23] X. M. Hu, J. Zhang, Y. Yu, Y. L. Li, X. N. Luo, and Y. H. Shi, "Hybrid genetic algorithm using a forward encoding scheme for lifetime maximization of wireless sensor networks," *IEEE Trans. Evol. Comput.*, vol. 14, no. 5, pp. 766-781, Oct. 2010.