Enhancing Lifetime Coverage in Wireless Sensor Networks: A Learning Automata Approach

Jakub Gąsior

Department of Mathematics and Natural Sciences
Cardinal Stefan Wyszyński University Warsaw Poland
j.gasior@uksw.edu.pl

Abstract. This paper focuses on enhancing the lifespan of the Wireless Sensor Networks (WSNs) by integrating a distributed Learning Automaton into its operation. The proposed framework seeks to determine an optimized activity schedule that extends the network's lifespan while ensuring that the monitoring of designated target areas meets predefined coverage requirements. The proposed algorithm harnesses the advantages of localized algorithms, including leveraging limited knowledge of neighboring nodes, fostering self-organization, and effectively prolonging the network's longevity while maintaining the required coverage ratio in the target field.

Keywords: Wireless sensor networks · Self-organization · Learning automata · Maximum lifetime coverage problem.

1 Introduction

Wireless Sensor Network (WSN) is a distributed network comprised of small, battery-powered devices, referred to as sensors, capable of sensing and collecting data from their surrounding environment. These sensors communicate with one another wirelessly using radio frequency waves and collaborate to perform specific tasks, such as monitoring environmental parameters like temperature, humidity, or air quality. Data is then collected and sent for further processing via a specialized sink node.

The sensors in WSNs are typically low-power and have limited computing capabilities, making energy efficiency a crucial aspect of their design. Lifetime optimization in WSNs refers to maximizing the duration of operation or the network lifetime of a WSN. The lifetime of a WSN is defined as the time elapsed between the deployment of the network and the time when the first node in the network runs out of energy.

This work will focus on the power management aspect of maximizing the lifetime of WSNs. Usually, a collective of sensors that oversee specific areas often display redundancy, where multiple sensors can cover the same monitored targets, and the forms of redundancy can vary. The optimal utilization of this redundancy within WSNs and determining the potential scheduling sequence of sensors is essential in prolonging the network's lifetime. Effectively resolving this coverage

ICCS Camera Ready Version 2024
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-63783-4_19

issue can lead to the indirect maximization of the WSN lifetime. Therefore, implementing scheduling schemes that alternately regulate the active and sleep states of the sensor nodes, also known as node wake-up scheduling protocols, is a viable technique for enhancing the network's lifetime.

We present a framework for building sensors' activity schedule that addresses the abovementioned challenges, building on the capabilities introduced in prior publications [1, 3]. The main contribution of this paper lies in developing and implementing a versatile, LA agent-based model supporting the optimal activity schedule of individual sensors, aiming to extend the network's autonomous lifetime.

The rest of this paper is organized as follows. We introduce the theoretical background of the problem and review related literature in Section 2. Section 3 describes our proposed optimization approach. We present the findings of our experiments in Section 4. The last section concludes the paper.

2 Theoretical background

We consider a WSN comprising N sensors $S = \{s_1, s_2, ..., s_N\}$ randomly deployed over a two-dimensional rectangular area of $x \times y$ $[m^2]$. The area contains M targets $T = \{t_1, t_2, ..., t_M\}$ (also called Points of Interest (POI)) that are uniformly distributed with a step of g. All sensors are assumed to have the same sensing range R_s^i and battery capacity b_i.

Each sensor can operate in one of two modes: an *active* mode when the battery is turned on, a unit of energy is consumed, and the POIs within its sensing range are monitored; and a *sleep* mode when the battery is turned off, and the POIs within its sensing range are not monitored.

The i-th sensor's mode during the j-th time interval is denoted by α_i^j, where $\alpha_i^j \in 0, 1$. A value of α_i^j equal to 1 indicates that the i-th sensor is in active mode during the j-th time interval, and 0 indicates that it is in sleep mode. Assuming that battery activation and deactivation occur at discrete time intervals, a quality of service (QoS) measure can be used to evaluate the performance of the WSN. The network coverage can be determined by the ratio of the number of POIs monitored by active sensors to the total number of POIs as follows:

$$COV(t_j) = \frac{|M|_{obs_j}}{|M|}. \tag{1}$$

At any given time, this ratio should not fall below a predetermined value of q $(0 < q \leq 1)$. While maintaining complete coverage of the area is desirable, achieving a high coverage ratio (80–90 %) may be more relevant in some cases. The lifetime of a WSN (further denoted as LF(q)) can be defined as the number of k consecutive time intervals t_j in the schedule during which the coverage of the target area is within a range of δ from a specified coverage ratio q, as follows:

$$LF(q) = \max\{k|(\forall j)\ j < k, \quad abs(COV(t_j) - q) \leq \delta\}. \tag{2}$$

ICCS Camera Ready Version 2024
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-63783-4_19

Multiple sensors can simultaneously detect the same point in the target area, enhancing data quality or reliability. However, this redundancy can also result in wasted energy [11]. In this study, we approach the point coverage problem in wireless sensor networks as a scheduling problem called the Maximum Lifetime Coverage Problem (MLCP). We aim to extend the network's lifetime by minimizing energy consumption and reducing the number of redundant sensors operating during each time interval.

2.1 Learning automata

A learning automaton is a self-operating mechanism that responds to a sequence of instructions in a certain way to achieve a particular goal. The automaton either responds to a predetermined set of rules or adapts to the environmental dynamics in which it operates [8].

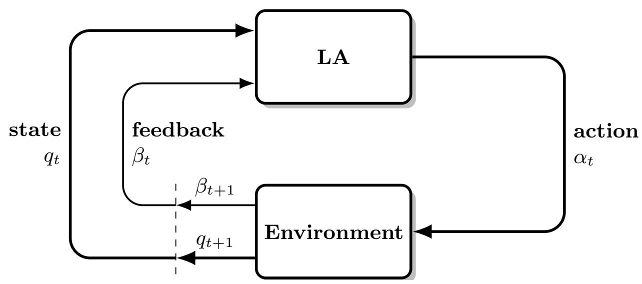


Fig. 1: A feedback loop of learning automata.

The learning process involving the Learning Automata (LA) and a random environment is presented in Fig. 1. Whenever an automaton generates an action α_t, the environment sends a response β_t either penalizing or rewarding the automaton with a specific probability c_i.

Generally, LA can be categorized as a fixed structure LA or a variable structure LA. This paper considers variable structure LA, where the action probability vector is not fixed, and the action probabilities are updated after each iteration. Thus, through interactions with the environment, LAs may adjust their action-selection probabilities by a positive reinforcement (i.e., Reward, Eq. (3)):

$$\begin{aligned} p_i(t+1) &= p_i(t) + a(1-p_i(t)) && j = i \\ p_j(t+1) &= (1-a)p_j(t) && \forall j, j \neq i \end{aligned} \tag{3}$$

or a negative reinforcement (i.e., Penalty, Eq. (4)):

$$\begin{aligned} p_i(t+1) &= (1-b)p_i(t) && j = i \\ p_j(t+1) &= \frac{b}{r-1} + (1-b)p_j(t) && \forall j, j \neq i \end{aligned} \tag{4}$$

ICCS Camera Ready Version 2024
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-63783-4_19

Values $p_i(t)$ and $p_j(t)$ are the probabilities of actions α_i and α_j at time t, r is the number of actions, while a and b are the reward and the penalty parameters, respectively. We employ a learning algorithm called *Linear Reward-Penalty* (L_{R-P}) with $a = b$ in our work [8].

2.2 Related work

In recent years, there has been a growing interest in developing distributed algorithms to address these challenges through reinforcement learning and automata models. [6] introduced an effective scheduling technique named LAML, leveraging learning automata. In this method, each node is equipped with a learning automaton, facilitating the selection of its appropriate state (active or asleep) at any given time.

Subsequently, this research was expanded in [7], where attention was directed toward addressing partial coverage challenges. This scenario involves continuous monitoring of a limited area of interest. The authors introduced the PCLA algorithm to deploy sleep scheduling strategies, demonstrating its effectiveness in selecting sensors efficiently to meet imposed constraints and ensuring favorable performance metrics, including time complexity, working-node ratio, scalability, and WSN lifetime.

In a recent development, [5] introduced an energy-efficient scheduling algorithm utilizing learning automata to address the target coverage problem. This approach allows sensor nodes to autonomously select their operational state. To validate the efficacy of their scheduling method, comprehensive simulations were conducted, comparing its performance against existing algorithms.

In another study, [4] presented a novel on-demand coverage-based self-deployment algorithm tailored for significant data perception in mobile sensing networks. The authors first extend the cellular automata model to accommodate the characteristics of mobile sensing nodes, resulting in a new mobile cellular automata model adept at characterizing spatial-temporal node evolution. Subsequently, leveraging learning automata theory and historical node movement data, they proposed a new mobile cellular learning automata model. This model empowered nodes to intelligently and adaptively determine optimal movement directions with minimal energy consumption.

In their study, [2] utilized a Learning Automata-based model as a routing mechanism in wireless sensor networks, aiming for enhanced energy efficiency and reliable data delivery. The approach aims to calculate the selection probability of the next node in a routing path based on various factors such as node score, link quality, and previous selection probability. Furthermore, they proposed an energy-efficient and reliable routing mechanism by combining learning automata with the A-star search algorithm.

Another contribution by [10] introduced a scheduling technique named Pursuit-LA. Each sensor node in the network was equipped with an LA agent to autonomously determine its operational state to achieve comprehensive target coverage at minimal energy cost.

ICCS Camera Ready Version 2024
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-63783-4_19

Lastly, [9] proposed a continuous learning automata-based approach for optimizing sensor angles in Distributed Sensor Networks (DSNs). The method involved continuously adapting sensing angles using LA models. Comparative analysis against a conventional automata-based approach demonstrated the efficacy of the proposed algorithm.

3 Automata-based approach to the WSN lifetime optimization

In this section, we introduce our proposed methodology. Every sensor node s_i is linked with an automaton LA_i in the setup phase. This automaton randomly chooses one of two available actions (0 - *sleep* or 1 - *active*) and disseminates this decision to n_i immediate neighbors (sensors sharing the same subset of Points of Interest). By the end of this phase, all sensor nodes in the network are informed about their neighboring nodes and the targets under surveillance.

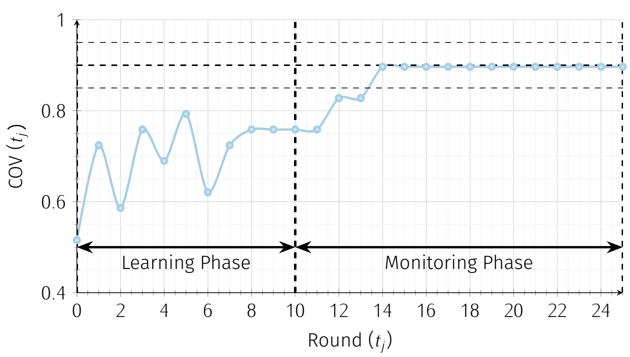


Fig. 2: Illustration of the LA-based WSN scheduling scheme consisting of a learning phase and an operation phase.

Upon completion of this phase, we advance to the learning phase. Here, each LA_i updates its action probability vector based on its chosen action and the actions of its immediate neighbors. Notably, an agent A_i can receive a reward (Eq. (3)) even if it remains inactive ($\alpha_i = 0$), thereby conserving its battery. This is feasible if neighboring sensors collectively cover shared Points of Interest (POIs), provided the number of uncovered POIs remains below a specified threshold value determined by the coverage parameter q. Conversely, if the coverage parameter is not met, the automaton will incur a penalty (Eq. (4)).

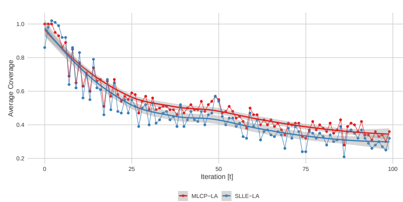
On the other hand, if an agent A_i opts to expend its battery energy to cover POIs, it may face penalties if neighboring sensors already cover the same subset of POIs. This introduces a trade-off between achieving the required coverage and preserving battery power. Based on this interaction, each node selects optimal

ICCS Camera Ready Version 2024
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-63783-4_19

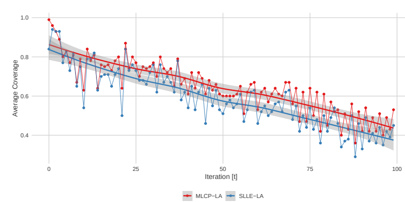
actions based on the acquired information, determining whether to remain active or become idle during the subsequent operation phase. Upon depletion of battery power by a group of sensors, the network must reorganize to restore the required level of coverage. This process is visualized in Fig. 2.

4 Experimental Study

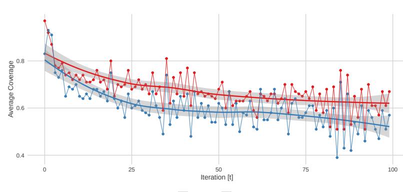
In this section, we aim to evaluate the effectiveness of the proposed algorithm through multiple computer simulations. To accomplish this, we will employ a fixed sensor network, where sensor nodes are randomly positioned within a $1000 : m \times 1000 : m$ area alongside a static deployment of 400 targets. The sensing range of sensors was set at a value of $R_s^i = 175$. The required coverage target was $q = 0.8$ with $\delta = 0.1$. The number of nodes will vary in the range $S = \{16, 36, 49, 100\}$ sensors. The simulations were conducted using Matlab's custom Wireless Sensor Network (WSN) simulator. The results were averaged over ten runs to ensure robustness. Through this evaluation, we seek insights into the algorithm's performance across diverse conditions.



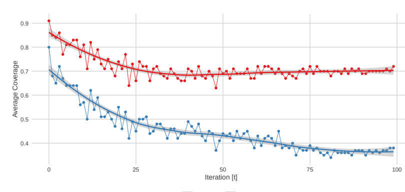
(a) $N = 16$ sensors



(b) $N = 36$ sensors



(c) $N = 49$ sensors



(d) $N = 100$ sensors

Fig. 3: Averaged results of the network coverage acquired by MLCP-LA (red) and SLLE-LA (blue) algorithms for variable number of sensors deployed over the target area with $T = 400$ POIs.

We begin with a comparison of the proposed approach (denoted as MLCP-LA) with our previous work (further denoted as SLLE-LA) presented in [1, 3]. The old solution employed a synchronized local leader election game model to replace

ICCS Camera Ready Version 2024
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-63783-4_19

a global optimization problem with a problem of searching for Nash equilibrium (NE) by a team of players participating in a non-cooperative game.

The average coverage ratio changes in successive iterations of the algorithm are presented in Fig. 3. The figure visualizes four sample runs of the two algorithms (MLCP-LA in red, SLLE-LA in blue) for WSNs comprised of $N = 16$ (Fig. 3(a)), $N = 36$ (Fig. 3(b)), $N = 49$ (Fig. 3(c)) and $N = 100$ (Fig. 3(d)) sensors, respectively.

In the case of the smaller networks ($N = 16$ and $N = 36$ sensors), the performance of both algorithms is similar, with a slight advantage to the proposed, fully decentralized LA-based solution. However, results become more varied with the rising complexity of the scheduling problem for WSN comprised of $N = 49$ and $N = 100$ sensors. Compared to previous experiments, we can observe more considerable differences in performance between analyzed scheduling solutions, especially in the case of an extensive network comprised of $N = 100$ sensors.

This behavior is mainly consistent with our expectations and the nature of both solutions. The solution presented in this work (MLCP-LA) is a fully decentralized algorithm enabling sensors to manage their sleep/activity cycles based on specific coverage goals. This algorithm has the advantages of being localized, utilizing limited knowledge of neighboring sensors, and self-reorganizing to preserve the required coverage ratio and prolong the WSN's lifetime.

While our other work (SLLE-LA) also employs the LA model as its primary learning loop, it requires further negotiation between players to achieve NE in each local neighborhood. While it does not present a problem for smaller networks, it is clear that SLLE-LA needs to be more scalable to compete in more extensive networks. Therefore, it is more advantageous for sensor networks when nodes learn what actions to take rather than follow a predefined schedule.

5 Conclusion

In this paper, we proposed an algorithm based on the concept of LA to solve MLCP in WSN. This algorithm has the advantages of being localized, utilizing limited knowledge of neighboring sensors, and self-reorganizing to preserve the required coverage ratio and prolong the WSN's lifetime.

Our early research findings demonstrate that the LA agents can achieve an effective solution in a completely decentralized fashion, minimizing battery expenditure and ultimately prolonging the lifetime of the WSNs. Compared to our older works, empirical data suggests that aligning the agents' objectives with the system goal is critical in achieving global efficiency in decentralized learning. Allowing each agent to pursue its objectives selfishly may result in a suboptimal solution. In contrast, we achieved global efficiency by requiring each agent to consider a small group of surrounding agents.

Future work will include studying additional reinforcement learning functions to find better solutions to the studied problem. For example, *Linear Reward-Epsilon-Penalty* when $b << a$ and *Linear Reward-Inaction* when $b = 0$. An additional study of the relation between the experimental parameters (density

ICCS Camera Ready Version 2024
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-63783-4_19

of sensors and targets, regularity of their distribution, variable sensing range of nodes, and battery levels) and the achieved coverage and lifetime results will follow.

Bibliography

[1] Gąsior, J., Seredyński, F.: A learning automata-based approach to lifetime optimization in wireless sensor networks. In: Artificial Intelligence and Soft Computing. pp. 371–380. Springer International Publishing (2021)

[2] Gudla, S., Kuda, N.R.: Learning automata based energy efficient and reliable data delivery routing mechanism in wireless sensor networks. Journal of King Saud University - Computer and Information Sciences 34(8, Part B), 5759–5765 (2022)

[3] Gąsior, J., Seredyński, F., Hoffmann, R.: Towards Self-organizing Sensor Networks: Game-Theoretic ϵ-Learning Automata-Based Approach. In: Cellular Automata - 13th International Conference on Cellular Automata for Research and Industry, ACRI 2018, Como, Italy, September 17-21, 2018, Proceedings. pp. 125–136 (2018)

[4] Lin, Y., Wang, X., Hao, F., Wang, L., Zhang, L., Zhao, R.: An on-demand coverage based self-deployment algorithm for big data perception in mobile sensing networks. Future Generation Computer Systems 82, 220–234 (2018)

[5] Manju, Chand, S., Kumar, B.: Target coverage heuristic based on learning automata in wireless sensor networks. IET Wireless Sensor Systems 8(3), 109–115 (2018)

[6] Mostafaei, H., Esnaashari, M., Meybodi, M.R.: A coverage monitoring algorithm based on learning automata for wireless sensor networks (2014)

[7] Mostafaei, H., Montieri, A., Persico, V., Pescapé, A.: A sleep scheduling approach based on learning automata for wsn partialcoverage. Journal of Network and Computer Applications 80, 67–78 (2017)

[8] Narendra, K.S., Thathachar, M.A.L.: Learning automata: an introduction. Prentice-Hall, Inc., USA (1989)

[9] Qarehkhani, A., Golsorkhtabaramiri, M., Mohamadi, H., Yadollahzadeh-Tabari, M.: Solving the target coverage problem in multilevel wireless networks capable of adjusting the sensing angle using continuous learning automata. IET Communications 16(2), 151–163 (2022)

[10] Upreti, R., Rauniyar, A., Kunwar, J., Haugerud, H., Engelstad, P., Yazidi, A.: Adaptive pursuit learning for energy-efficient target coverage in wireless sensor networks. Concurrency and Computation: Practice and Experience 34(7) (2022)

[11] Yetgin, H., Cheung, K.T.K., El-Hajjar, M., Hanzo, L.H.: A survey of network lifetime maximization techniques in wireless sensor networks. IEEE Communications Surveys Tutorials 19(2), 828–854 (2017)

ICCS Camera Ready Version 2024
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-63783-4_19