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LETTER

Genetic algorithm optimization of sensor placement for CO2 concentration observation

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Abstract In our previous studies, we introduced a method for determining the optimal sensor placement of wireless sensor networks for monitoring indoor carbon dioxide (CO2) concentrations. This method, based on brute force, has proven to be accurate and reliable. However, the computational complexity increases exponentially with an increase in the number of sensors. Therefore, this study proposes a novel approach for optimal sensor node placement based on a genetic algorithm (GA) that offers a more efficient alternative to the brute force method. By utilizing the GA, we achieved optimal sensor placement with reduced computational complexity. To validate the effectiveness of our GA based method, we conducted numerical experiments using observed CO2 concentration. The results demonstrate that our proposed approach not only achieves optimal sensor placement but also maintains the accuracy of the observations.

Keywords: wireless sensor networks, optimal placement, CO2 concentration, genetic algorithm
Classification: Wireless communication technologies

1. Introduction

Indoor ventilation has become increasingly significant not only for mitigating aerosol transmission of diseases such as COVID-19 but also for preventing airborne infections, such as tuberculosis, measles, and varicella. It is crucial for maintaining indoor air quality and ensuring a healthy living environment. Monitoring carbon dioxide (CO2) concentration serves as a key to determining the timing of ventilation. This can be achieved through Internet of Things (IoT) systems, which are utilized for several applications, such as environmental monitoring [1] and operational status management in factories [2]. The wireless sensor network [3] is fundamental technology within IoT systems.

The wireless sensor networks comprise several gateways and a lot of sensors with wireless communication capabilities. While increasing the number of sensors can enhance the accuracy of observations, it also increases costs. Therefore, determining the optimal placement that reduces costs by minimizing the number of sensors while maintaining observation accuracy is crucial. For indoor CO2 concentration monitoring, an optimal sensor placement method based on brute force has been proposed [4]. This approach involves grouping a lot of sensors placed beforehand with similar observations based on cross correlation coefficients and relative errors. By identifying sensors with comparable readings, the number of sensors can be reduced without compromising observation accuracy. However, although the brute force based approach can determine the optimal placement, the computational complexity of the algorithm increases exponentially as the number of sensors placed beforehand increases.

This study proposes a sensor placement method based on genetic algorithm (GA) [5] to address the issue of an exponential increase in computation time with an increase in the computational complexity can be achieved. Furthermore, the proposed algorithm not only decreases the computational complexity but also enhances solution accuracy by grouping sensors based on similar observations from other sensors. This method enables the efficient and accurate determination of optimal sensor placements in wireless sensor networks with numerous sensors.

The remainder of this letter is organized as follows: Section 2 describes the proposed GA based optimal sensor placement method. In Section 3, computer simulation results of the proposed method based on actual observations of CO2 concentration. Finally, section 4 concludes this letter.

2. GA based optimal sensor placement

2.1 Conventional method

First, the conventional method of optimal sensor placement is presented [4]. This method involves pre-placing a lot of sensors to determine the optimal placement of sensors. Conventionally, the optimal placement is determined based on the observation $x_k(n)$ at the kth sensors. We let S denote the set of all sensors, with $M = |S|$, where M is the total number of sensors. Furthermore, we let C_k and M_k denote the set of similarity sensors for the kth sensors and $M_k = |C_k|$. C_k is given by:

$$C_k = \left\{ l_1, \cdots, l_{M_k} | l_1, \cdots, l_{M_k} \in S, r_{k,l_i} \leq \lambda_r \vee \epsilon_{k,l_i} \leq \lambda_\epsilon \right\} \quad k, l = 1, \cdots, M, \quad i = 1, \cdots, M_k, \tag{1}$$

where l_i, λ_r, and λ_ϵ are the ith similarity sensor, threshold of the cross correlation coefficient, and threshold of the relative error, respectively. Furthermore, $r_{k,l}$ and $\epsilon_{k,l}$ are the cross correlation coefficient and relative error between $x_k(n)$ and $x_l(n)$, respectively, and are given by:

$$r_{k,l} = \frac{\sum_{n=1}^{N} \{x_k(n) - \overline{x_k}\} \{x_l(n) - \overline{x_l}\}}{\sqrt{\sum_{n=1}^{N} \{x_k(n) - \overline{x_k}\}^2} \sqrt{\sum_{n=1}^{N} \{x_l(n) - \overline{x_l}\}^2}}, \quad k, l = 1, \cdots, M, \tag{2}$$

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$$\epsilon_{k,l} = \frac{1}{N}\sum_{n=1}^{N}\left|\frac{x_k(n) - x_l(n)}{x_k(n)}\right|, \quad k,l = 1,\cdots,M, \tag{3}$$

where N is the number of observations. In [4], the minimum required number of sensors L is derived based on brute force to satisfy the following equation:

$$S = \bigcup_{i=1}^{L} C_{\gamma_i}, \tag{4}$$

where γ_i is the ith sensor in the set of L sensors. The brute force based method allows for the identification of the optimal combination among the representative solutions by selecting the smallest average of $\epsilon_{\mathrm{k,l}}$s.

2.2 Proposed GA based optimal placement method

In this subsection, the proposed GA based optimal placement method is presented. To describe the proposed method, first, independent sensors and non-independent sensors are defined. The independent sensors are that their observations do not similar to those of other sensors, meaning $M_k = 1$. We let We let S_{I} denote the set of independent sensors, and $M_{\mathrm{I}} = |S_{\mathrm{I}}|$ is the total number of independent sensors. Then, S_{I} can be written as:

$$S_{\mathrm{I}} = \left\{a_1,\cdots,a_{M_{\mathrm{I}}}|a_1,\cdots,a_{M_{\mathrm{I}}} \in S, M_{a_k} = 0\right\}$$
$$k = 1,\cdots,M_{\mathrm{I}}, \tag{5}$$

where a_k is the kth independent sensor. We let S_{NI} denote the set of non-independent sensors, and $M_{\mathrm{NI}} = |S_{\mathrm{NI}}|$ is the total number of non-independent sensors, and $M = M_{\mathrm{I}} + M_{\mathrm{NI}}$. S_{NI} can be written as:

$$S_{\mathrm{NI}} = \left\{b_1,\cdots,b_{M_{\mathrm{NI}}}|b_1,\cdots,b_{M_{\mathrm{NI}}} \in S, M_{b_k} \geq 1\right\}$$
$$k = 1,\cdots,M_{\mathrm{NI}}. \tag{6}$$

Next, the proposed method is presented. As shown in eq. (5), the independent sensors are that their observations do not similar to those of other sensors, making it impossible to complement their observations with others. Therefore, all independent sensors must be included in the optimal placement. This implies that determining the optimal placement for S involves identifying the optimal placement for S_{NI} after distinguishing S into S_{I} and S_{NI}. We let L_{OPT} and $L_{\mathrm{NI\text{-}OPT}}$ denote the number of optimal sensors for S and S_{NI}, respectively, with $L_{\mathrm{OPT}} \geq L_{\mathrm{NI\text{-}OPT}}$, where equality holds when $M_{\mathrm{I}} = 0$.

From these, it can be seen that the optimal sensors are selected from $\binom{M_{\mathrm{NI}}}{L_{\mathrm{NI\text{-}OPT}}}$ combinations when making the distinction, whereas they are selected from $\binom{M}{L_{\mathrm{OPT}}}$ combinations in the absence of the distinction. Therefore,

$$\binom{M}{L_{\mathrm{OPT}}} \geq \binom{M_{\mathrm{NI}}}{L_{\mathrm{NI\text{-}OPT}}}, \tag{7}$$

where equality also holds when $M_{\mathrm{I}} = 0$.

The proposed GA based optimal placement method is shown in Fig. 1. In Fig. 1, according to which the cross correlation coefficient $r_{k,l}$ and relative error $\epsilon_{k,l}$ are computed from all observations, with sensors distinguished into the independent S_{I} and non-independent sensors S_{NI}. In the algorithm, an individual of length G is defined as a combination of sensors, with each sensor represented by gene, The length G is incremented by one during the optimization process. GA is employed to determine the optimal sensor placement using individuals with length G. If the optimal solution cannot be determined when the generation exceeds T_{G}, then G is incremented by one.

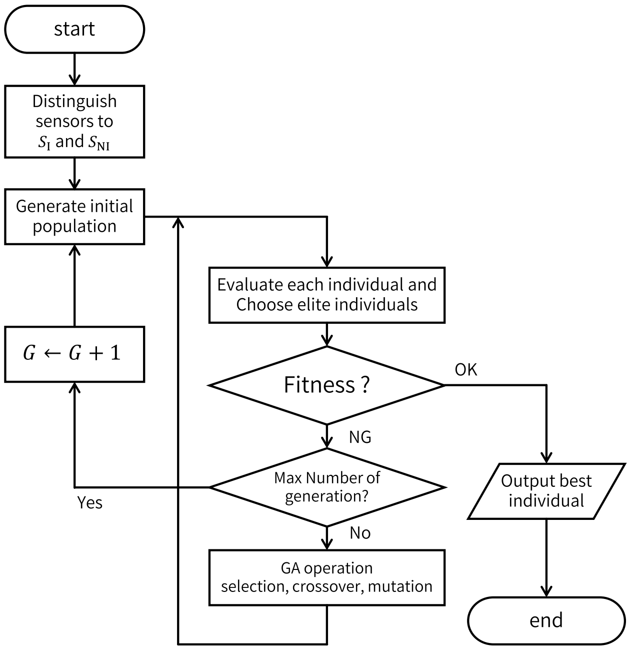

Fig. 1 Algorithm for proposed GA based optimal placement method.

3. Experimental evaluation

3.1 Experimental setup

The experimental evaluation is executed in a laboratory at Mie University, as shown in Fig. 2. A gateway is placed on the bookshelf and 32 ($M = 32$) sensors are placed beforehand in the experimental field. The details of their placement beforehand are shown in Fig. 3. The configurations of the sensor and gateway are shown in Fig. 4. The gateway is configured in Raspberry Pi 3 B+, LoRa module, and RX antenna, whereas the sensor is configured in Raspberry Pi zero, CO2 sensor, LoRa module, mobile battery, and TX antenna. Raspberry Pi zero manages the CO2 sensor and LoRa module. In the network, we utilize long range (LoRa) communications in the sub-GHz band [6] to send observations at the sensor. LoRa is a low power wide area (LPWA) communication standard commonly used in wireless infrastructures for IoT applications. Previous studies have demonstrated the effectiveness of LoRa in both outdoor and indoor environments [7, 8]. In addition, the sub-GHz band LPWA is particularly suitable for our application owing to its lower utilization compared with the 2.4 GHz band. Each sensor observes CO2 concentration at half-hourly intervals and transmits the sensor number, observation time, and CO2 concentration to the gateway. To prevent packet collisions among sensors, each sensor transmits them with a time delay equal to the sensor number multiplied by 10 s. The gateway collects the sensor observations, and the optimal

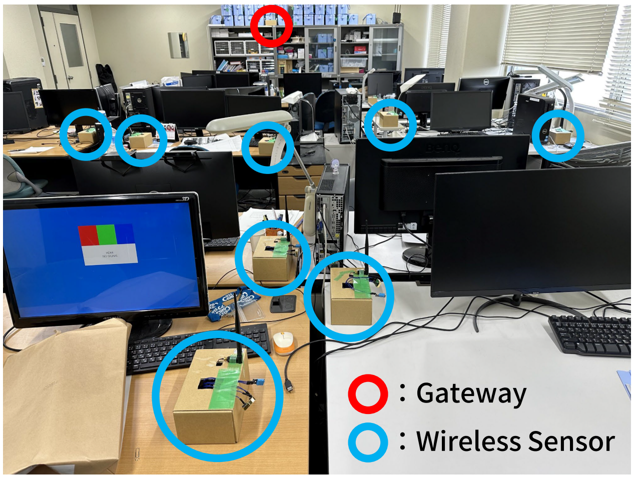

Fig. 2 Overview of experimental field

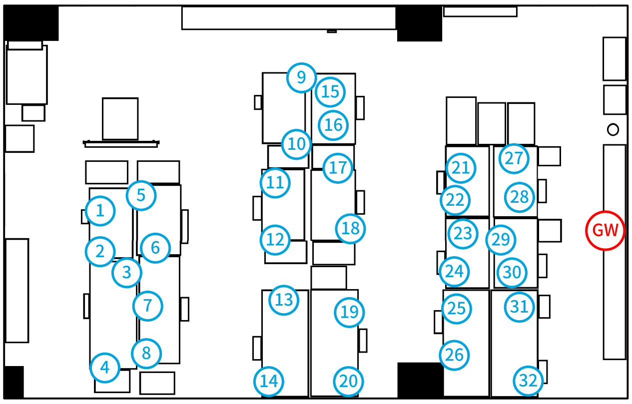

Fig. 3 Sensor placement beforehand in experimental field.

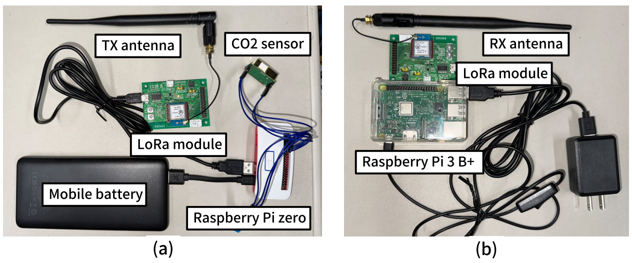

Fig. 4 Configurations of (a) Sensor and (b) Gateway for CO_2 concentration measurement. The sensor measures CO_2 levels and sends data to the gateway, which collects and manages the data.

sensor placement is determined based on collected observations. Two experiments are conducted under the conditions shown in previous 1) from Nov. 30, 2022 to Dec. 2, 2022 and 2) from Jun. 7, 2023 to Jun. 9, 2023.

For the proposed algorithm, the initial population size is set at 50 individuals and a maximum generation limit for each G is set at $T_G = 50$, starting at $G = 2$. In GA, the elitist preservation strategy is employed, allowing up to 1 individuals to be carried over to the next generation. Two-point crossover is employed and mutation is not implemented. Furthermore, the optimization process is executed on a computer with Intel Core i5-12600k CPU and 16GB RAM.

Table I Evaluation results of proposed method

Parameters	**Observation (1)**	**Observation (2)**
Optimal placement (one case)	2, 13, 26, 31, 32	17, 20, 27, 31
Independent sensors	26, 32	27, 31
Computation time		
Proposed method	0.0114 s	0.17152 ms
Proposed w/o distinction	0.0436 s	0.02599 s
Brute force based method	0.1288 s	0.04284 s

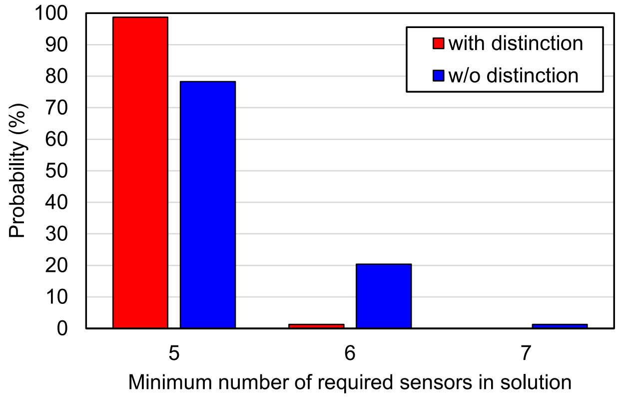

Fig. 5 Accuracy of optimization result for observation (1).

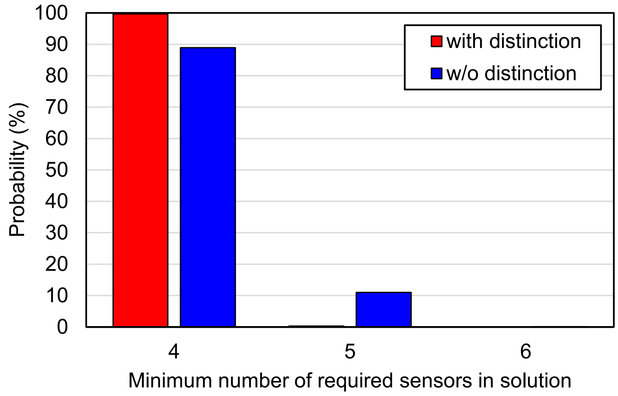

Fig. 6 Accuracy of optimization result for observation (2).

3.2 Experimental results

First, the optimization results based on observed CO_2 concentrations in the experiment are shown in Table I. These results have been validated against the brute force based method, confirming their accuracy. As shown in Table I, for observation (1), a computation time of the proposed method is 0.0114 s whereas that of the brute force based method is 0.12881 s, demonstrating a significant reduction in the computation time. Furthermore, the proposed method without the distinction between the independent sensors and non-independent sensors is 0.0436 s, and it can be seen that the proposed method is effective the reduction of the computation time. Furthermore, the optimization results for observation (2) are shown in Table I. As shown in the results for the computation time, it is similar tendency of the results for observation (2). In both figures, the number of required sensors in the optimization results are shown.

Finally, the accuracy of the distinction between the independent and non-independent sensors is evaluated. Figures 5 and 6 show the accuracy of the optimization results for and both observations (1) and (2), respectively. Note that the minimum number of required sensors for both observations (1) and (2) are 5 and 4, respectively. As shown in Fig. 5, the proposed method with the distinction between the independent sensors and non-independent sensors can obtain the optimal combination with the minimum number of required sensors, approximately 100 % of the time. However, the proposed method without the distinction only achieves the optimal combination with the minimum number of required sensors, approximately 80 % of the time. Furthermore, as shown in Fig. 6, further demonstrating the effectiveness of the proposed GA based optimal sensor placement method.

4. Conclusion

This study investigated the GA based sensor placement optimization method for the observation of CO2 concentration. The proposed method can reduce the computational complexity of the conventional brute force based method while maintaining accuracy in optimization results. By distinguishing between independent and non-independent sensors prior to optimization, the computational complexity of the proposed method was further reduced. The effectiveness of the proposed method was evaluated using actual CO2 concentration observations in an indoor environment, validating its efficacy in sensor placement optimization.

Future works involve the verification for the scalability of the proposed method. Although the proposed method can be expected the reduction of the computational cost to obtain the optimal sensor placement in large-scale sensor networks not limited to observation fields and environmental parameters to be observed, the lack of empirical experiments to support this claim limits the verification. This conducts to require the large number of experiments in large-scale sensor networks; however, it is difficult to obtain the experimental results because the costs associated with carrying out a sufficient number of the experiments for a robust evaluation are significant. Therefore, the evaluation method of optimization algorithms is required in such sensor networks, along with the experiments in large-scale sensor networks.

Acknowledgments

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