International Journal of Disaster Risk Science (2024) 15:107–115
https://doi.org/10.1007/s13753-024-00546-w

www.ijdrs.com
www.springer.com/13753

ARTICLE

# Design of Resilient Sensor Networks Balancing Resilience and Efficiency

**Sergey N. Vecherin[1] · Kiril D. Ratmanski[2] · Luke Hogewood[2] · Igor Linkov[2]**

Accepted: 1 February 2024 / Published online: 1 March 2024


**Abstract**
In recent years, the notion of resilience has been developed and applied in many technical areas, becoming exceptionally pertinent to disaster risk science. During a disaster situation, accurate sensing information is the key to efficient recovery efforts. In general, resilience aims to minimize the impact of disruptions to systems through the fast recovery of critical functionality, but resilient design may require redundancy and could increase costs. In this article, we describe a method based on binary linear programming for sensor network design balancing efficiency with resilience. The application of the developed framework is demonstrated for the case of interior building surveillance utilizing infrared sensors in both two- and three-dimensional spaces. The method provides optimal sensor placement, taking into account critical functionality and a desired level of resilience and considering sensor type and availability. The problem formulation, resilience requirements, and application of the optimization algorithm are described in detail. Analysis of sensor locations with and without resilience requirements shows that resilient configuration requires redundancy in number of sensors and their intelligent placement. Both tasks are successfully solved by the described method, which can be applied to strengthen the resilience of sensor networks by design. The proposed methodology is suitable for large-scale optimization problems with many sensors and extensive coverage areas.

**Keywords** Binary linear programming · Optimal sensor placement · Redundant networks · Resilience and efficiency · Resilient sensor networks

## 1 Introduction

In modern engineered systems, cyber and physical components have been increasingly integrated for the purpose of monitoring and control. Advances in sensor hardware and networks have been critical to this development, as sensors form the key linkage between the cyber and physical domains. In this way, sensors are often the key source for real-time disaster risk information and can detect functional degradation when disasters occur. These advances have greatly increased the number of potential data streams available for users to analyze. They have been accompanied by the rise of increasingly advanced analytical methods such as artificial intelligence, machine learning, and digital twins. As the capacity to draw insights from more complex and heterogeneous data sources has improved, advanced sensor networks have become nearly ubiquitous in applications across diverse domains from intruder detection to power and water system monitoring.

However, with this increased cross-domain integration also come new and poorly understood threats that may cascade and propagate in unexpected ways (Xing 2021). Sensors in particular are vulnerable to attacks in both the cyber (for example, cyberattacks) and physical domains (for example, targeted attacks, natural hazards and disasters). The vulnerability at the data source can have downstream impacts on disaster response and recovery. At the same time, the design of sensor networks tends to focus on how to make a given system operate more efficiently under normal conditions. In this stable environment, efficiency is the primary concern, typically in terms of maximizing coverage with minimal sensors (Dhillon and Chakrabarty

✉ Sergey N. Vecherin
Sergey.N.Vecherin@usace.army.mil

[1] Cold Regions Research and Engineering Laboratory, Engineering Research and Development Center, Hanover, NH 03755, USA

[2] Environmental Laboratory, Engineering Research and Development Center, Vicksburg, MS 39180, USA

2003; Vecherin et al. 2011). But, in such highly optimized sensor networks, a disruption to even a single sensor can lead to missing information and failure to detect anomalies. Thus, while sensors are crucial for disaster detection and response, they are also vulnerable to these same events. Applications of advanced sensor networks should accept that disruptions to the network will occur. Instead of working to minimize or eliminate all risks, developers must plan for resilience, designing sensor networks to absorb and quickly recover from disruption.

The idea of resilient engineering, including sensing design, has rapidly evolved from theoretical concepts (Hollnagel et al. 2006; Woods 2015) to practical applications and engineering designs (Hollnagel et al. 2006; Patriarca et al. 2018). Resilience thinking accepts that disruptions and disasters will inevitably occur, and, instead of shielding the system from threat or hardening to reduce vulnerabilities, focuses on the ability to maintain or quickly recover critical systemic functionality (Linkov and Trump 2019). This can be accomplished by designing systems either to be resilient (that is, "resilience by design") or to bring external resources to recover critical functionality through "resilience by intervention" (Linkov et al. 2021). Traditionally, security has been the primary way that sensor developers have dealt with risk. Given the threats that modern systems face, designers must move beyond traditional security considerations to plan to be resilient.

This article describes a method for designing wireless sensor networks (WSNs) that balances efficiency and resilience. This method is applied to the problem of placing infrared (IR) sensors in an interior setting for the sake of intruder detection. The method provides locations for sensor nodes so that the desired, user-specified level of coverage and network resilience are both achieved with a minimal number of sensors. To achieve this objective, we (1) define resilience in the context of disaster risk science; (2) introduce the notion of "depth of resilience"; (3) formulate the problem in terms of the binary linear programming problem; (4) show how to apply a previously developed algorithm for fast approximate solution to the considered case; and (5) provide a comparative analysis of the results to evaluate the quality of the solution. While the applied algorithm was adopted from prior work (Vecherin et al. 2011, 2017), its application to the considered task in the context of sensor network resilience and analysis of the results are novel contributions to the field.

We begin with a discussion of existing literature on resilient sensors and sensor networks. We then describe the algorithm for the resilient and efficient placement of sensors in two-dimensional (2D) and three-dimensional (3D) space. Finally, future research areas are identified that are important for the continued advancement of resilience within sensor networks.

## 2 Resilience of Sensor Networks

The National Academies defines resilience as the ability to "plan for, absorb, recover from, or more successfully adapt to actual or potential adverse events" (National Academies et al. 2012, p. 16). In this article, the focus is on the first two aspects of resilience, namely, "to plan for and absorb." The objective is to determine such sensor locations that would preserve WSN functionality if some sensors were disabled (hence, "absorb" the disruption). This can be thought of at the system level, where the primary focus is the persistent delivery of a system's critical function, as opposed to the hardening of a specific asset to resist failure. Linkov et al. (2013) proposed a resilience matrix framework that divides resilience into the four temporal domains defined by the National Academies (plan, absorb, recover, adapt), as well as into the four components of network-centric operations: physical, information, cognitive, and social. Within an integrated cyber-physical system, sensors are key for ensuring access to the information domain through all stages of a disaster. Furthermore, sensors can be impacted by threats in the physical domain, while threats to cyber operations can impact the cognitive ability of decision makers to process and understand data collected from sensors. In this way, sensor networks have cross-cutting impacts on and relationship with the different components of resilience, requiring further research on methods for the resilient design of sensor networks.

Generally, research on the resilience of sensors and sensor networks is fairly limited, with most studies focusing on only one aspect of resilience. Security is the most common risk-minimization strategy for sensors, with many methods such as key assignment applied to secure sensor networks from threats (Yang et al. 2005). While strengthening security is an important part of the planning phase for the sake of mitigating risk, it cannot be assumed to protect against all forms of risk (Ali et al. 2018). Other studies address the fault-tolerance of sensors, such as the introduction of a clustering method for energy efficient routing of data through a wireless sensor network (Gupta and Younis 2003). Similarly, some work addresses the reliability of sensors under disruption (Li and Ouyang 2012). While both concepts are related to mitigating risks and absorbing disruptions, resilience focuses on critical functionality more holistically, and should also consider the ability to recover lost critical function of the network. The literature on sensor resilience was reviewed in this context to identify the resilience phase of past work focus and presented in Table 1.

Because of the broad role wireless sensor networks play across network-centric operations, it is necessary to consider their resilience at all levels of the system. This is

**Table 1** Categorization of existing literature on resilience of sensor networks

| Papers | Resilience | | | | Sensing Subsystem | | | |
|---|---|---|---|---|---|---|---|---|
| | Plan | Absorb | Recover | Adapt | Sensor | Processing | Communi-cation | Power Supply |
| Yoo et al. (2020) | | x | | | x | | | |
| Bush et al. (2005) | x | x | | | | | x | x |
| Song et al. (2007) | x | x | | | | | x | |
| Burbano et al. (2021) | x | x | | | | x | x | |
| Ueyama et al. (2014) | | | x | | x | | | |
| Ganesan et al. (2001) | | x | | | | | x | x |
| Ali et al. (2018) | x | x | | | | | x | |
| Zhao (2016) | x | x | | | | | x | |
| Guidoni et al. (2010) | | x | | | | | x | |
| Del-Valle-Soto et al. (2015) | | x | | | | x | x | |
| Lee and Younis (2010) | | | x | | | | x | |
| Li and Ouyang (2012) | x | x | | | x | | x | |
| Huang et al. (2020) | x | x | | | | | x | |
| Yang et al. (2005) | x | | | | | | x | |
| Zhang et al. (2020) | | x | | | x | | | |
| Nikolopoulos and Makropoulos (2023) | | x | | | x | | | |
| Vecherin et al. (2011, 2017) | x | x | x | | x | | x | |
| Ratmanski and Vecherin (2022) | x | x | x | | x | | x | |

Papers are organized first by their focus within resilience, then by which subsystem of sensor networks they address

largely divided into subsystems of the sensor domain: sensor hardware, processing, communication, and power supply (Akyildiz et al. 2002). In the context of sensor network resilience, the bulk of research has focused on resilient communication networks. This manifests in several studies such as improving path-routing algorithms (Ganesan et al. 2001; Bush et al. 2005), or designing the network structure to maintain functionality during disruption, which also provides a useful definition of resilience as "the capacity of a network to provide and maintain an acceptable quality of service (specified by the user and/or network designer) in the presence of faults" (Guidoni et al. 2010, p. 1266). At the same time, more emphasis in future work must address the additional need to quickly recover a failed network to an acceptable level of service when faults do occur. Furthermore, this definition is applied only to the computing network itself, but sensors have a physical hardware component often ignored in network-based studies.

In sensor research, the optimal placement of sensor hardware is an important design criterion, typically based on efficiency only. Research on the resilience of sensors, however, focuses primarily on the communication network and not on the physical arrangement of sensors. One study examined the optimization of sensor placement within a water quality sensor network for resilience by measuring how overall relative performance changes with disrupted sensors (Nikolopoulos and Makropoulos 2023). Further developments are needed to extend these methods to assess the recovery of sensors. Furthermore, more research is necessary on the physical placement of sensors within a network in order to ensure resilience of WSNs at a system level.

To incorporate the concept of "resilience by design" into sensor networks, this article advances a methodology for optimizing the placement of sensors by taking resilience as well as efficiency into account. Conventionally, the sensor placement problem centers on minimizing a desired objective (for example, the number of sensors) to achieve the specified level of coverage. However, in this most efficient case, disabling any single sensor leads to loss of coverage in a certain area, and therefore potentially a degradation in the critical functionality of the entire network. Incorporating additional sensors can introduce redundancy to the system such that if one sensor fails, particularly in a high-interest area, another sensor will still be in place to collect data. These additional sensors come with additional resource costs, making it cost-prohibitive to have a fully redundant or resilient network. Balancing the trade-offs between these two objectives, in the user-controlled way, is the goal of the method proposed here.

## 3 Method

The most common approaches to the optimal sensor placement problem are based on combinatorial optimization, random placement (cheap sensors, open large areas), or heuristic placement strategies. An extensive overview of the approaches is provided in prior work related to sensor placement (Vecherin et al. 2011). The problem can be considered as a generalization of the art gallery problem, where a minimal number and position of guards need to be determined in order for each painting of the gallery to be seen by at least one guard. In previous iterations of similar work (Vecherin et al. 2011, 2017), the authors discussed the evolution and generalization of the art gallery problem towards the sensor placement problem, including both heuristic approaches and strictly formulated optimization formulations, along with the underlying assumptions and restrictions. The core approach in this article is based on the algorithm described in Vecherin et al. (2011, 2017), which is a fast algorithm providing an approximate solution to the binary linear programming problem formulated for sensor performance in the probabilistic framework. However, the details of its application to the considered task and analysis of the solutions with and without resilience constraints were not explored previously. Before presenting the algorithm for an approximate solution in Sect. 3.3, it is necessary to introduce a strict formulation of the optimization problem in the next subsection.

### 3.1 Binary Linear Programming Formulation for Optimal Sensor Placement

In this approach, the performance of any sensor is characterized in terms of the probability of detection $P_d$ and the probability of false alarm $P_{fa}$. Although the original model (Vecherin et al. 2011) allows one to specify $P_{fa}$ as a function of sensor location, in this article a typical and convenient choice of a constant $P_{fa}$ is made. Along with information about noise energy probability density functions, $P_{fa}$ determines the value of threshold of signal detection by a sensor, which, along with the signal energy probability density function, allows for calculation of the probability of signal detection $P_d(\mathbf{r}, \mathbf{r}_s)$ at location $\mathbf{r}$ by a sensor at location $\mathbf{r}_s$.

Another parameter that needs to be specified for each location where coverage is required is a desired minimal probability of detection $P_{pr}(\mathbf{r})$. A remarkable flexibility that the probabilistic sensor performance characterization provides is that there may exist configurations where no single sensor achieves or exceeds the desired probability of detection $P_{pr}(\mathbf{r})$, while the network achieves this as a whole. As was discussed in Vecherin et al. (2011), requiring "coverage by at least one sensor" in a probabilistic sense leads to a different and more efficient sensor network design when compared to the requirement where for any given point there must be a specific sensor that has a desired probability of detection at that point. In fact, having determined the above $P_d(\mathbf{r}, \mathbf{r}_s)$ for all point-sensor pairs, one can require that the joint probability $P_{md}(\mathbf{r};\mathbf{r}_1, \dots, \mathbf{r}_M)$ of all sensors failing to detect a signal at $\mathbf{r}$ to be less than $1 - P_{pr}(\mathbf{r})$. This follows from the fact that joint probabilities are a product of the marginal probabilities for independent random variables:

$$P_{md}\left(\mathbf{r};\mathbf{r}_1, \dots, \mathbf{r}_M\right) = \prod_{S=1}^{M} P_{md}\left(\mathbf{r};\mathbf{r}_s\right), \tag{1}$$

where $P_{md}\left(\mathbf{r};\mathbf{r}_s\right) = 1 - P_d(\mathbf{r}, \mathbf{r}_s)$ is the probability that a single sensor located at $\mathbf{r}_s$ fails to detect a signal at $\mathbf{r}$. This is equivalent to the original requirement $P_d\left(\mathbf{r};\mathbf{r}_1, \dots, \mathbf{r}_M\right) \geq P_{pr}(\mathbf{r})$, where $P_d\left(\mathbf{r};\mathbf{r}_1, \dots, \mathbf{r}_M\right) = 1 - P_{md}(\mathbf{r};\mathbf{r}_1, \dots, \mathbf{r}_M)$ is the probability of signal detection at $\mathbf{r}$ by at least one sensor.

Taking the logarithm on both sides of the inequality corresponding to the above requirements, one can convert the product into the summation, and yield the following condition for each point $\mathbf{r}$:

$$\sum_{s=1}^{M} \ln(P_{md}\left(\mathbf{r};\mathbf{r}_s\right)) \leq \ln\left(1 - P_{pr}(\mathbf{r})\right). \tag{2}$$

Denoting the total number of possible source locations as $Q$ and sensor locations as $K$, the set of conditions for all points that now need to be satisfied can be written in matrix notation:

$$\mathbf{Ap} \leq \mathbf{b}, \tag{3}$$

where:

$\mathbf{p}_{K\times1}$ is a binary column vector with only possible values of 0 or 1, where a value of 1 indicates the placement of a sensor at that location;

$\mathbf{b}_{Q\times1}$ is a preference vector, where $b_k = \ln(1 - P_{pr}(\mathbf{r}_k))$;

$\mathbf{A}_{Q\times K}$ is a coverage matrix, where $A_{is} = \ln P_{md}(\mathbf{r}_i, \mathbf{r}_s)$.

The problem of optimal sensor placement can now be formulated as the following binary linear programming problem:

$$\mathbf{p}_0 = \operatorname{argmin} \mathbf{c}^T\mathbf{p}, \mathbf{Ap} \leq \mathbf{b}, p_n = \{0, 1\}, n = 1, .., K. \tag{4}$$

Here, $\mathbf{c}_{K\times1}$ is a cost column-vector, which can represent a monetary value, power consumption, or sensor installation time. Setting all values of $\mathbf{c}$ to 1 will result in a solution $\mathbf{p}_0$ having a minimal number of sensors required to cover the area with the prescribed probability of detection or greater. As explained in Vecherin et al. (2017), the formulation can be extended to various situations including distinct types of sensors, limited sensor availability, obstacles and forbidden areas, and wireless sensor communication.

### 3.2 Approximate Fast Solution for Minimal Number of Sensors

The approximate solution to the binary linear programming problem Eq. 4 is presented for the case where vector $\mathbf{c} = (1, 1, ..., 1)^T$. In other words, we will be focusing on minimizing the total number of sensors to cover a desired area. The discussion about feasibility of the optimization problem, and step-by-step layout of the approximate solution algorithm is covered in Vecherin et al. (2011). A rigorous solution of this nondeterministic polynomial-time complete (NP-complete) problem rapidly becomes too computationally intensive and cannot be applied for practically relevant cases, as shown in Vecherin et al. (2017). The main idea of the fast approximate algorithm is to do a consecutive search, avoiding considering all possible combinations. At each step, there is a decision vector $\mathbf{p}$ with elements corresponding to spatial locations where sensors can be placed. If some of its entries equal one, a sensor is placed in that location; if zero, no sensor is placed. The algorithm will look for the best position to put another sensor in the vector $\mathbf{p}$. Letting $\hat{\mathbf{p}}$ be a trial vector with an extra 1 added consecutively to all possible sensor locations, which correspond to zeros in the vector $\mathbf{p}$, the best position to place another sensor is the one that would minimize the sum of the positive elements of $\Delta(\hat{\mathbf{p}}) = \mathbf{A}\hat{\mathbf{p}} - \mathbf{b}$:

$$\mathbf{p} = \text{argmin} \sum_i \Delta_i(\hat{\mathbf{p}}), i \in \{1, ..., Q, \text{s.t. } \Delta_i(\hat{\mathbf{p}}) > 0\}. \tag{5}$$

Note that the algorithm stops either when adding extra 1 results in no positive elements of $\Delta(\hat{\mathbf{p}})$ (that is, coverage is achieved at all required locations $\mathbf{r}_1, ..., \mathbf{r}_Q$), or when there are no more candidate sensor locations, when $\hat{\mathbf{p}} = (1, 1, ..., 1)^T$, or when there are no more sensors (for the problem with a finite sensor supply). In this case, if the coverage is still unsatisfactory, the problem is infeasible. In the latter case, however, the algorithm still produces a sensor placement that can be considered the best possible coverage of the area given insufficient resources. As shown in Vecherin et al. (2017), this algorithm yields a very practical solution for many scenarios, including large-scale problems with tens of thousands of decision-making variables, in a few seconds using a conventional laptop, while the exact solution in many cases cannot be obtained at all due to the complexity of the problem.

### 3.3 Resilient Sensor Placement

As mentioned above, one of the approaches in the paradigm of resilience is "resilience by design." In the case of sensor networks, designed resilience can be accomplished by incorporating calculated redundancy into the network design such that if a certain number of sensors are disabled, the remaining sensors would still provide the required coverage, that is, the desired detection probability would still be satisfied for desired locations. The locations where redundancy is required will be referred as "resilience points" hereafter. In addition, the "depth of resilience," $D$, indicates how many sensors in a network can be disabled without loss of coverage. As an example, let depth of resilience be $D$ for all resilient points (without too much loss of generality, we assume the same depth for all resilience points, although it can be defined individually for every single point of interest). Then all resilience points need to be covered by at least $R = D + 1$ sensors to allow any $D$ of them to be disabled without loss of coverage. As described in Vecherin et al. (2017), this requirement can be incorporated into the existing binary linear programming framework Eq. 4 by modifying a row $i$ of $\mathbf{A}$ and $\mathbf{b}$, corresponding to resilience point $\mathbf{r}_i$, as follows:

$$A_{is} = \{-1, \text{if} P_d(\mathbf{r}_i, \mathbf{r}_s) \geq P_{pr}(\mathbf{r}_i), s = 1, ..., K, \\ \text{otherwise: } b_i = -R. \tag{6}$$

Since the rest of the rows of $\mathbf{A}$ and $\mathbf{b}$ will remain unmodified, the corresponding remaining points will be covered in the previously discussed probabilistic sense. The condition for changing the coverage matrix element $A_{is}$ to -1 indicates whether that specific sensor covers a designated location or not. If yes, the entry is changed to –1. Therefore, condition in Eq. 3 will be satisfied only if more than or exactly $R$ sensors cover the designated location, which is a desirable result.

Similar to Eq. 4, the formulation for resilient sensor networks given by Eq. 6 is rigorous in a mathematical sense. However, some care should be exercised in implementing Eq. 6 in the approximate algorithm Eq. 5, which places sensors consecutively one by one, regarding weighting of the preferences at each step and resolving issues of multiple choices for the exact same criterion value. These issues are discussed in Ratmanski and Vecherin (2022).

## 4 Results

The problem considered in this section is to monitor human presence at a workplace in a large building for safety reasons. For this purpose, commercial infrared sensors with realistic sensor performance characteristics will be used (Panasonic Corp. 2023).

Note that the optimal sensor placement framework is applicable to both two- and three-dimensional spaces. Indeed, in all equations, particular location vectors $\mathbf{r}$ and $\mathbf{r}_s$ can represent both 2D and 3D vectors. We consider both cases below.

The floorplan subject to monitoring is shown in Fig. 1. It is a complex coverage scene with multiple obstacles, which includes offices, hallways, stairs, meeting rooms, and cubicles. Here, the area filled in green color is the area where coverage is required in the 2D problem, which is, essentially, hallways and corridors, excluding cubicles and offices. For the 3D problem, cubicle spaces will also be covered.

To characterize sensor coverage in a probabilistic sense, we introduced a smooth function for the probability of detection so that it matches vendor sensor specifications.

Figure 2 shows a one-dimensional spatial section at locations $\mathbf{r} = (x, 0)$ of the resulting probability of detection by a sensor located at the origin, $\mathbf{r}_s = (0, 0)$. The red line represents the idealized sensor coverage pattern with a sharp detection boundary, while the blue line represents a more realistic probability of detection, with a transitioning zone. We took the intersection between the two curves to correspond to probability of detection 0.95 at the vendor specified coverage diameter of 3.6 m. The probability of false alarm was set to $10^{-6}$.

In the 2D problem, the candidate sensor locations are set along the walls inside the coverage area (indicated by red color in Fig. 1) to avoid sensor placement in the middle of a corridor. Also, without loss of generality, it is assumed that each sensor has an omnidirectional 2D field of view. Examples of sensor optimal placement with a finite 2D field of view can be found in Ratmanski and Vecherin (2022).

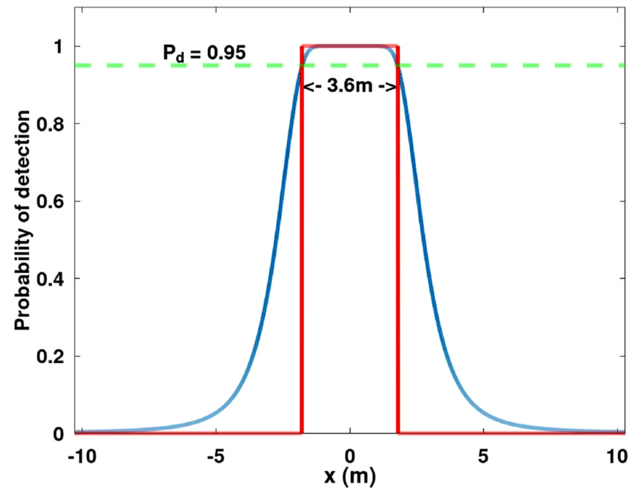


**Fig. 2** One-dimensional spatial section of probability of detection by an idealized (red curve) and a realistic (blue curve) sensor. Probability of detection $P_d = 1$ indicates spatial locations completely covered by a sensor located at $x = 0$.

Figure 3 shows optimal sensor placement for the 2D problem when only efficiency is required. The sensor supply was limited to 17 sensors. This number was chosen because it covered most, but not all critical intersections in the building. Red color indicates areas where the probability of detection

**Fig. 1** Workplace floor plan, with desired coverage area for the 2D problem depicted in green color. For the 3D problem, the interior of cubicles (large rectangular rooms outlined by the corridors in green color) is subject to coverage as well.

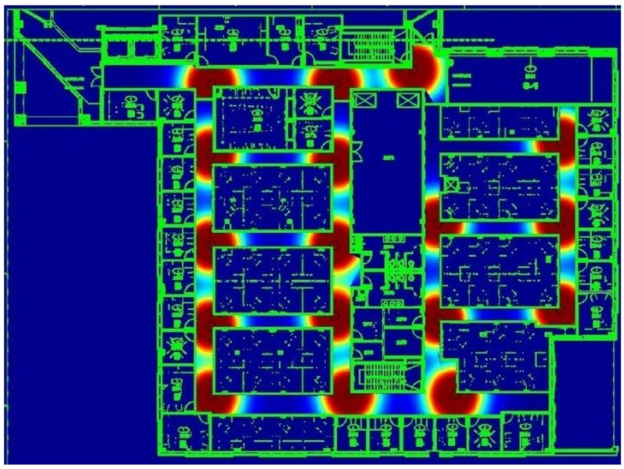

**Fig. 3** Optimal sensor placement by 17 sensors (black circles), without resilience, with each sensor's effective coverage diameter of 3.6 m

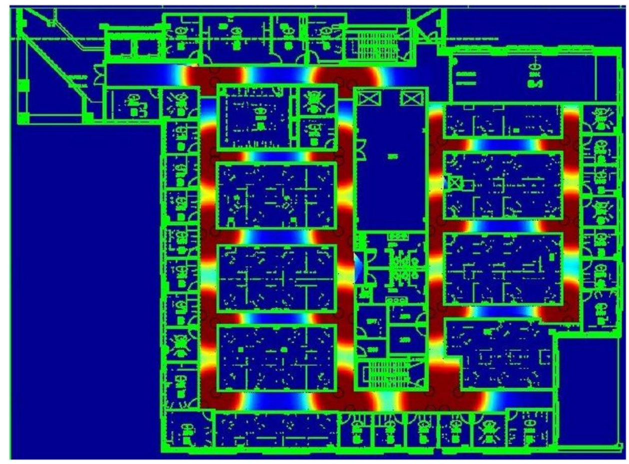

**Fig. 4** Optimal sensor placement by 36 sensors (black circles), with the depth of resilience $D = 1$, with each sensor effective coverage diameter of 3.6 m

is high, satisfying the coverage preferences, $P_{pr} = 0.95$ at $P_{fa} = 10^{-6}$. As one can see, the algorithm places sensors at the corners of the walls, the only locations providing maximum coverage at the intersections of the corridors. In this example, such an optimal arrangement is intuitively accepted and understood. However, in more complex scenarios with obstacles, sensor placement in prohibited areas, and so on, an optimal placement may not be inferred intuitively.

Also, note that limiting the sensor supply to 17 sensors makes the problem infeasible in the rigorous mathematical sense, meaning that it is an insufficient number of sensors to provide the required coverage of every location in the area of interest. However, the suggested placement is still the best possible for this limited sensor supply. This is a distinguished feature of the approximate algorithm Eq. 5, because any strict algorithm would render the problem infeasible, without any solution.

Let us now impose a requirement for optimal sensor placement with the depth of resilience $D = 1$; that is, every location of interest should be covered by at least two sensors (so that any one of them can be disabled without affecting critical functionality). In this case, one would expect that the suggested placement will be on the adjacent corners or opposite walls, covering approximately the same area to provide the needed redundancy (resilience) to provide necessary coverage, even when one sensor is disabled. Figure 4 confirms this intuitive guess. For this scenario, the total number of available sensors was limited to 36.

As one can see from the considered examples, the proposed method achieves quite satisfactory results in the 2D case.

In the 3D problem, there are three modifications of the optimization conditions. First, the candidate sensor locations are no longer limited to walls. Instead, the entire ceiling in the room is eligible for placing a sensor. Second, the sensors have a finite field of view in 3D, which results in the omnidirectional field of view in the 2D horizontal plane. Third, cubicles have low wall heights so that a sensor located on the ceiling can see the cubicle interior. For that reason, in a 2D view from above, the cubicle walls can be treated as transparent. Figures 5 and 6 show optimal location of sensors without and with resilience, $D = 1$, for the 3D case.

As seen in Figs. 5 and 6, there is intuitive justification in both optimization cases for the suggested locations. In the non-resilient case, Fig. 5, in the horizontal plane, 25

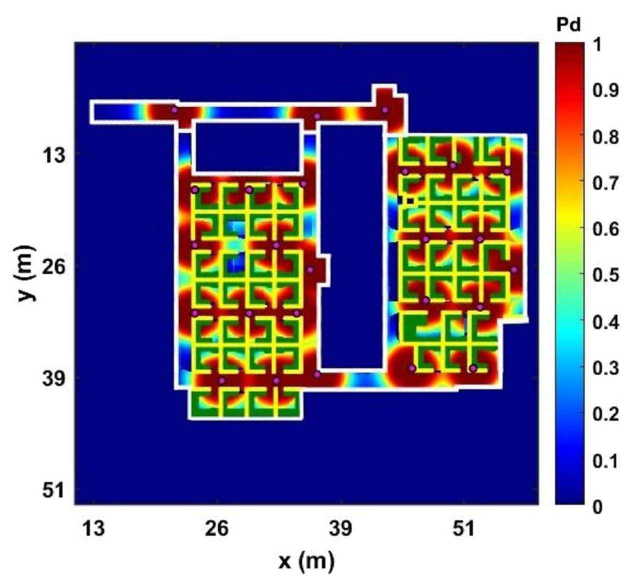


**Fig. 5** Optimal sensor placement by 25 sensors (black circles) without resilience for the 3D case, view from above. The cubicle walls are short so that sensors can see the interior of cubicles. Dark green color depicts office desks.

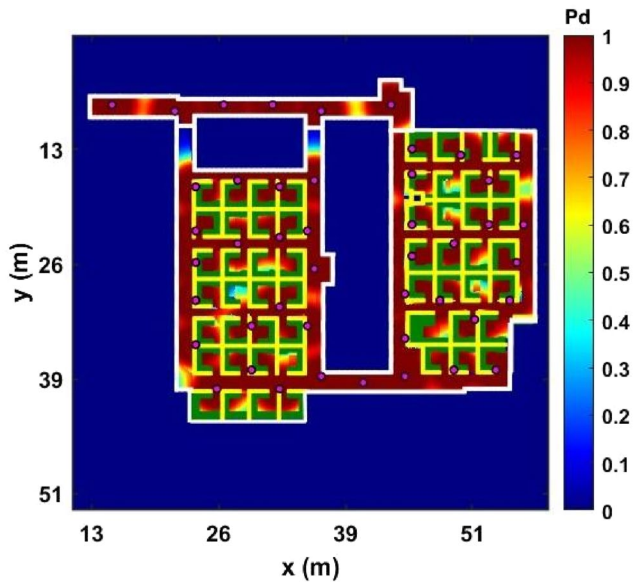


**Fig. 6** Optimal sensor placement by 45 sensors (black circles) with the depth of resilience $D = 1$ for the 3D case, view from above. The cubicle walls are short so that sensors can see the interior of cubicles. Dark green color depicts office desks.

sensors are located at intersections and corners, which provide the maximum coverage on the floor. In the redundant case, Fig. 6, 45 sensors are located almost uniformly over the possible candidate location area on the office ceiling, which maximizes coverage area and, at the same time, provides the required depth of resilience.

## 5 Discussion and Conclusion

To be able to face the threats of the future, sensor hardware and networks must be designed with resilience in mind. This resilience will require a compromise with the goals of efficiency, given the potential for additional resource costs incurred by adding sensors. By balancing both efficiency and resilience optimization, the framework proposed here seeks to address the challenges of this delicate trade-off. Intuitively, redundancy could be achieved by simply doubling the number of sensors in the efficient case. However, this will not address the question of where these additional sensors should be placed, nor what type of sensors to use (in the case of multi-modal sensor networks). Moreover, such a guess will not guarantee the required coverage. The situation will be more challenging in a more complex area, requiring hundreds of sensors. The results show the value of this algorithm that can optimize for resilience while reducing the cost of adding too many sensors. The details of problem formulation, application of the algorithm, and analysis of the results with and without resilience constraints were not examined in prior work. Furthermore, while the considered application addresses the problem of physical security against intruders, it is designed to be adaptable to many different problems. For example, in other systems, such as power and water networks, maintaining sensor coverage is critical, since missed data collection could fail to detect disruptions and lead to catastrophic failure of the system. In this way, resilient sensor placement can ensure power and water monitoring, and control systems are able to continue functioning even during a disaster, when they are most necessary.

To advance resilience applications for sensor networks, further research is required in several areas. The described methodology is focused on the absorption of disruptions, so that disabling one or more sensors does not lead to the loss of WSN functionality. Future research efforts could tackle adaptivity and recovery aspects of resilience in WSN. This research should center on ensuring the resilience of cyber-physical systems as a whole. In this context, sensors may not just deliver information to end users, but could inform an automated response by the system to automatically recover from a threat. Technologies such as edge computing have the potential to further strengthen system resilience through redundancy in their computing nodes, in the same fashion as redundant sensors. Furthermore, maintaining the ability to process data collected from sensors through artificial intelligence or digital twin tools will require fast optimization solutions, particularly when a decision maker response is required during a disruption. In all these related areas, developers must move away from the traditional focus on efficiency and consider how to assess and incorporate resilience into system design. By incorporating resilience into all levels of cyber-physical monitoring and control systems, users can be better prepared to maintain or recover functionality in the face of disasters.

**Acknowledgments** This work was funded by the Integrating Energy and Computing Networks project funded through the USACE Military Programs. Permission to publish was granted by the Director, Cold Regions Research and Engineering Laboratory.



## References

Akyildiz, I.F., W. Su, Y. Sankarasubramaniam, and E. Cayirci. 2002. Wireless sensor networks: A survey. *Computer Networks* 38(4): 393–422.

Ali, S., T. Al Balushi, Z. Nadir, and O.K. Hussain. 2018. Improving the resilience of wireless sensor networks against security threats: A survey and open research issues. *International Journal of Technology* 9(4): Article 828.

Burbano, L., L.F. Combita, N. Quijano, and S. Rueda. 2021. Dynamic data integration for resilience to sensor attacks in multi-agent systems. *IEEE Access* 9: 31236–31245.

Bush, L.A., C.D. Carothers, and B.K. Szymanski. 2005. Algorithm for optimizing energy use and path resilience in sensor networks. In *Proceedings of the Second European Workshop on Wireless Sensor Networks*. Istanbul, Turkey: IEEE, 391–96.

Del-Valle-Soto, C., C. Mex-Perera, R. Monroy, and J. Nolazco-Flores. 2015. On the routing protocol influence on the resilience of wireless sensor networks to jamming attacks. *Sensors* 15(4): 7619–7649.

Dhillon, S.S., and K. Chakrabarty. 2003. Sensor placement for effective coverage and surveillance in distributed sensor networks. In *2003 IEEE Wireless Communications and Networking 3*, 1609–1614. New Orleans, LA: IEEE.

Ganesan, D., R. Govindan, S. Shenker, and D. Estrin. 2001. Highly resilient, energy-efficient multipath routing in wireless sensor networks. *ACM SIGMOBILE Mobile Computing and Communications Review* 5(4): 11–25.

Guidoni, D.L., R.A.F. Mini, and A.A.F. Loureiro. 2010. On the design of resilient heterogeneous wireless sensor networks based on small world concepts. *Computer Networks* 54(8): 1266–1281.

Gupta, G., and M. Younis. 2003. Fault-tolerant clustering of wireless sensor networks. In *Proceedings of 2003 IEEE Wireless Communications and Networking*, 16–20 March 2003, New Orleans, LA, USA, 1579–1584.

Hollnagel, E., D. Woods, and N. Leveson, eds. 2006. In *Resilience engineering: Concepts and precepts*. Hampshire, UK: Ashgate Publishing Ltd.

Huang, R., L. Ma, G. Zhai, J. He, X. Chu, and H. Yan. 2020. Resilient routing mechanism for wireless sensor networks with deep learning link reliability prediction. *IEEE Access* 8: 64857–64872.

Lee, S., and M. Younis. 2010. Recovery from multiple simultaneous failures in wireless sensor networks using minimum Steiner tree. *Journal of Parallel and Distributed Computing* 70(5): 525–536.

Li, X., and Y. Ouyang. 2012. Reliable traffic sensor deployment under probabilistic disruptions and generalized surveillance effectiveness measures. *Operations Research* 60(5): 1183–1198.

Linkov, I., D.A. Eisenberg, M.E. Bates, D. Chang, M. Convertino, J.H. Allen, S.E. Flynn, and T.P. Seager. 2013. Measurable resilience for actionable policy. *Environmental Science & Technology* 47(18): 10108–10110.

Linkov, I., and B.D. Trump. 2019. *The science and practice of resilience*. Cham, Switzerland: Springer Nature Switzerland AG.

Linkov, I., B.D. Trump, M. Golan, and J.M. Keisler. 2021. Enhancing resilience in post-COVID societies: By design or by intervention?. *Environmental Science & Technology* 55(8): 4202–4204.

National Academies Committee on Increasing National Resilience to Hazards and Disasters, Committee on Science, Engineering, and Public Policy, and Policy and Global Affairs. 2012. *Disaster resilience: A national imperative*. Washington, DC: National Academies Press.

Nikolopoulos, D., and C. Makropoulos. 2023. A novel cyber-physical resilience-based strategy for water quality sensor placement in water distribution networks. *Urban Water Journal* 20(3): 278–297.

Panasonic Corp. 2023. *Grid-eye thermopile array solutions*. Panasonic Industrial Devices Sales Company of America. https://api.pim.na.industrial.panasonic.com/file_stream/main/fileversion/4112. Accessed 4 Aug 2023.

Patriarca, R., J. Bergström, G.D. Gravio, and F. Costantino. 2018. Resilience engineering: Current status of the research and future challenges. *Safety Science* 102: 79–100.

Ratmanski, K., and S. Vecherin. 2022. Resilience in distributed sensor networks. In *Infrared imaging systems: Design, analysis, modeling, and testing XXXIII*, ed. G.C. Holst, and D.P. Haefner, 31. Orlando, USA: SPIE.

Song, H., S. Zhu, and G. Cao. 2007. Attack-resilient time synchronization for wireless sensor networks. *Ad Hoc Networks* 5(1): 112–125.

Ueyama, J., H. Freitas, B.S. Faical, G.P.R. Filho, P. Fini, G. Pessin, P.H. Gomes, and L.A. Villas. 2014. Exploiting the use of unmanned aerial vehicles to provide resilience in wireless sensor networks. *IEEE Communications Magazine* 52(12): 81–87.

Vecherin, S.N., D.K. Wilson, and C.L. Pettit. 2011. Optimal sensor placement with signal propagation effects and inhomogeneous coverage preferences. *International Journal of Sensor Networks* 9(2): Article 107.

Vecherin, S.N., D.K. Wilson, and C.L. Pettit. 2017. Optimisation of numbers, types, and locations of wireless sensors with communication, finite supply, and multiple-sensor coverage constraints. *International Journal of Sensor Networks* 23(4): Article 222.

Woods, D.D. 2015. Four concepts for resilience and the implications for the future of resilience engineering. *Reliability Engineering & System Safety* 141(9): 5–9.

Xing, L. 2021. Cascading failures in Internet of Things: Review and perspectives on reliability and resilience. *IEEE Internet of Things Journal* 8(1): 44–64.

Yang, H., F. Ye, Y. Yuan, S. Lu, and W. Arbaugh. 2005. Toward resilient security in wireless sensor networks. In *Proceedings of the 6th ACM International Symposium on Mobile Ad Hoc Networking and Computing*. Urbana-Champaign, IL, USA: ACM, 34–45.

Yoo, M., T. Kim, J.T. Yoon, Y. Kim, S. Kim, and B.D. Youn. 2020. A resilience measure formulation that considers sensor faults. *Reliability Engineering & System Safety* 199(7): Article 106393.

Zhang, Q., F. Zheng, Z. Kapelan, D. Savic, G. He, and Y. Ma. 2020. Assessing the global resilience of water quality sensor placement strategies within water distribution systems. *Water Research* 172(4): Article 115527.

Zhao, J. 2016. On resilience and connectivity of secure wireless sensor networks under node capture attacks. *IEEE Transactions on Information Forensics and Security* 12(3): 557–571.