Optimization of sensor placement for gas leak detection in commercial areas

6: OPTIMIZATION OF SENSOR PLACEMENT FOR GAS LEAK DETECTION IN COMMERCIAL AREAS

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Abstract – This paper investigates the optimization problem of sensor placement based on distance measurements for acoustic underwater target localization. A sensor placement method based on distance measurements is proposed to enhance the accuracy and reliability of underwater target localization.

Keywords**:** Gas leak detection;Sensor placement optimization; Particle swarm algorithm;CFD simulation

1. INTRODUCTION

In commercial enclosed areas, the safety risks associated with natural gas leaks are particularly significant. Natural gas, primarily composed of methane, is highly flammable and explosive. At certain concentrations, when mixed with air, natural gas forms a combustible mixture that can explode upon contact with an ignition source. Moreover, since natural gas is colorless and odorless in its raw state, leaks are often difficult to detect timely. To enhance detection, artificially added sulfur compounds such as hydrogen sulfide can serve as odor indicators, although this method is not always effective in certain situations. Furthermore, natural gas leaks can also lead to a reduction in oxygen levels in enclosed spaces, posing a risk of suffocation. Although natural gas itself is not very toxic, trace harmful substances it carries, such as carbon monoxide, can also pose a health threat with prolonged exposure.

Existing optimizations of sensor placements do not specifically address indoor gas leak detection sensors. Gas leak detection sensors are particularly important due to their high safety requirements. This paper explores a sensor placement optimization method that combines greedy algorithms with Particle Swarm Optimization (PSO). The greedy algorithm provides initial optimization based on given risk values, setting the stage for the PSO, reducing subjective assessments of the number of sensors needed, and helping the PSO avoid local optima. The PSO ultimately addresses the challenges posed by the varying shapes of walls in commercial buildings and the complex paths of gas diffusion in enclosed spaces. Using the Gaussian plume diffusion model to simulate gas diffusion, it designs a layout plan constrained by specified detection times, concentration levels, and maximum placement distances, verifying its accuracy.

A sensor placement method based on discrete particle swarm optimization algorithm is developed by Kong, Cai, Liu, Zhu, Liu + 4 another authors [1], which evaluates fault propagation and sensor response time through a simulation model, thereby achieving fast convergence speed and optimization results. Furthermore, their method shows significant advantages in reducing the number of sensors and data redundancy, especially in a real case application of a subsea blowout preventer control system, demonstrating the practicality and effectiveness of their method.

Some literature reveals various methods and approaches toward optimizing sensor placement for environmental monitoring, highlighting the dynamic nature of this field. A paper by Aydin, Hagedooren, Rutten, Delsman, Essink + two another authors explored the optimization of salinity sensor placement within a polder network, employing a greedy algorithm [2]. The study primarily focused on the estimation of unmeasured salinity levels in main polder channels, using root mean square error (RMSE) as a metric for "goodness of fit". Their method integrated a hydrodynamic and salt transport model with principal component analysis (PCA), which proved effective in reducing model complexity while capturing significant salinity dynamics across the network. The placement of just three optimally positioned sensors, determined by the algorithm, was shown to robustly model and measure errors, approaching a global optimum identified through exhaustive search methods.

In exploring optimal sensor placement for structural health monitoring, significant advances have been made to refine methodologies that balance sensor efficiency and comprehensive coverage. Notably, Liu, Yan, Soraes delved into various sensor placement strategies tailored for modal identification, introducing an innovative minimal root mean square (Min-RMS) algorithm [3]. This method stands out by minimizing the RMS value over the mass-weighted modal assurance criterion (MMAC), which optimally positions sensors to capture critical modal information while mitigating measurement noise and model uncertainty. Their approach employs a thorough analysis involving both cantilever beams and jacket-platform models, providing a robust evaluation of sensor performance across multiple criteria, including modal orthogonality and system independence.

In the domain of sensor placement and maintenance optimization within process networks, the recent study I reviewed introduces a mathematical programming model that strategically identifies the optimal measurement locations and the precise number of redundant and spare sensors required for an effective corrective maintenance program which proposed by Ko and Chen [4]. This model is designed to maximize system availability while adhering to predefined constraints on life-cycle costs and the precision of estimators. To solve this complex optimization problem, the researchers employed genetic algorithms, leveraging their evolutionary capabilities to efficiently navigate the solution space. This method's efficacy was validated through comprehensive case studies, demonstrating its practical applicability and robustness in enhancing maintenance strategies and system reliability.

In the field of mobile sensor networks for target tracking, the study by Martínez and Bullo provides a comprehensive examination of optimal sensor placement and motion coordination strategies [5]. Their work focuses on the determinant of the Fisher Information Matrix to evaluate the optimal configuration of range sensors for both 2D and 3D cases, achieving a global optimum in the 2D scenario. They developed decentralized motion coordination algorithms that effectively direct the mobile sensor network towards an optimal arrangement, which is crucial for enhancing the performance of target tracking systems, particularly when using an extended Kalman filter. This research is pivotal as it bridges the gap between theoretical sensor placement and practical application in dynamic environments, offering valuable insights into decentralized control and the sensitivity maximization of sensor networks.

In the context of my dissertation on sensor placement for 3-D time-of-arrival target localization, the study by Xu, Ou, and Wu presents a comprehensive exploration of optimal sensor deployment strategies using the A-optimality criterion [6]. This criterion minimizes the trace of the inverse Fisher Information Matrix (FIM), facilitating enhanced estimation accuracy in 3D spaces. Their methodological innovation introduces two novel closed-form solutions for determining optimal sensor geometries, addressing both uniform and non-uniform measurement noise scenarios without constraints on sensor number, elevation, or target range.

Moreover, In the field of sensor placement for multistatic narrowband systems, Kreucher's work provides significant insights into optimizing the deployment of a sensor constellation to enhance target localization and tracking efficiency [7]. This study uniquely applies the posterior Cramér-Rao lower bound (PCRLB) to compute and minimize localization errors based on sensor positions within a non-Gaussian and nonlinear pixelated sensor model. Notably, the research incorporates practical elements like antenna beam patterns and target impulse responses to tailor sensor placements, significantly advancing the theory into applicable strategies for real-world scenarios.

In examining advancements in underwater target localization, the study by Moreno-Salinas, Pascoal, and Aranda offers a pivotal contribution through its exploration of optimal sensor placement for acoustic underwater target positioning using range-only measurements [8]. Their approach maximizes the Fisher Information Matrix (FIM) determinant to achieve the best possible estimator precision for 3D target positioning. This method is particularly notable for its use of a theoretical estimation framework to calculate the optimal sensor configurations, with variations considered for specific operational constraints like sensor placement and target depth.

2. METHODS AND PROCEDURES

To optimize the placement of sensors while reducing computational load and increasing computational speed, the blueprint is segmented into different zones based on varying risk values. A combined approach using greedy algorithms and PSO is employed for optimizing sensor positions. The greedy algorithm provides preliminary optimizations that serve as initial conditions for the subsequent PSO. The results are obtained through the PSO, which incorporates the Gaussian plume diffusion model to simulate gas dispersion effectively.

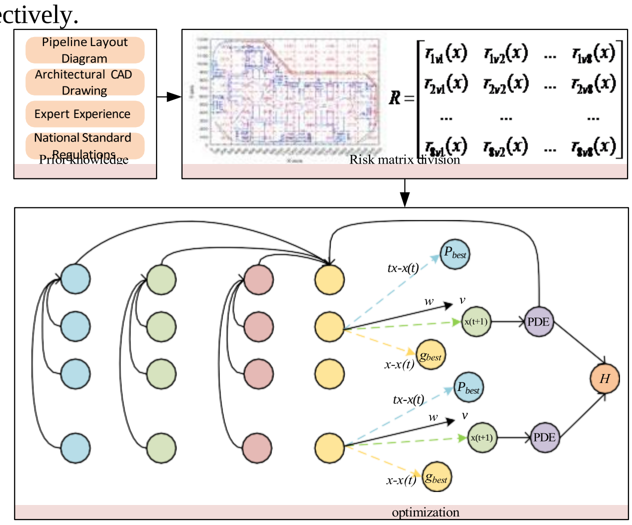

Figure 2-1: Overall Methodology Diagram

2.1. *Drawing Pre-processing*

In this study, image processing techniques are employed to pre-process the floor plans of commercial areas. Using edge detection and image segmentation techniques, key infrastructures such as walls and pipelines are identified, setting spatial constraints for the sensor layout. In the MATLAB environment, the floor plans are divided into an 8x8 grid, allowing detailed risk assessments for each cell. A comprehensive risk matrix is constructed, providing crucial data for the optimization of sensor placement.

$$R = \begin{bmatrix} r_{1v1}(x) & r_{1v2}(x) & \cdots & r_{1v8}(x) \\ r_{2v1}(x) & r_{2v2}(x) & \cdots & r_{2v8}(x) \\ \cdots & \cdots & \cdots & \cdots \\ r_{8v1}(x) & r_{8v2}(x) & \cdots & r_{8v8}(x) \end{bmatrix} \quad (2\text{-}1)$$

2.2. *Risk Classification and Initial Sensor Allocation*

Based on the risk matrix, risk value X is categorized into four levels, and according to these levels, an initial number of sensors is allocated to each area. A multi-level decision-making approach is employed to provide preliminary guidelines for the quantity and layout of the sensors. This method helps to ensure that the sensors are distributed efficiently, prioritizing areas with higher risk to maximize detection capabilities and resource allocation

Table 1. Relationship diagram between risk levels and sensors.

X	Risk Level	Number of sensors
75≤S<100	Low risk	0
50≤S<75	Medium risk	1
25≤S<50	Higher risk	2
0≤S<25	High risk	3

2.3. *Preliminary optimization of greedy algorithm*

In the optimization process of this study, a greedy algorithm is initially used for layout optimization.

Specifically, n points are randomly selected on the map, and one of these points is chosen as the initial position P for a sensor. The algorithm then iterates through these points, calculating their distances from sensor position P, and adds the furthest point to the sensor layout list. This process is repeated until a predetermined coverage rate is achieved. Through this method, a preliminary sensor placement plan can be quickly obtained. Although this plan does not fully consider the effects of wall diffusion, it sufficiently serves as a starting condition for the PSO, reducing the randomness in the generation of initial conditions for the PSO. The rough coverage range of the sensors is as follows:

$$G = S \times T \quad (2\text{-}2)$$

Where S represents the running speed of the gas; T represents the alarm time when the sensor receives the gas.

2.4. *Layout Optimization of PSO*

Based on the greedy algorithm, the PSO algorithm is used for a more refined optimization of sensor layout. The key functions used in this process include the coverage count function and the coverage rate function. The coverage count function calculates the coverage based on the target area's longitudinal and latitudinal coordinates (m and n), while the coverage rate function assesses the overall coverage based on the total number of sensors N and the side lengths of the target area (L1 and L2)..The coverage count function is:

$$C = \begin{cases} 1, D \le R. \\ 0, D > R \end{cases} \quad (2\text{-}3)$$

Where m is the horizontal coordinate of the target area; n is the vertical coordinate of the target area.

The coverage rate function is:

$$Z = \sum_{i=1}^{N} \frac{\sum_{m=1}^{L} \sum_{n=1}^{L} C(m, n)}{L_1 * L_2} \quad (2\text{-}4)$$

Where N represents the total number of sensors; L_1 and L_2 represent the side lengths of the target area.

The core of the optimization lies in adjusting the fitness function, which is the sensor coverage rate function, to achieve multi-objective optimization: maintaining a minimum distance of over 25 meters between each sensor, while minimizing the number of sensors used and maximizing area coverage. The PSO function is:

$$v_i^{(t+1)} = w \cdot v_i^{(t)} + c_1 \cdot r_1 \cdot (p_{best,i} - x_i^{(t)}) + c_2 \cdot r_2 (g_{best} - x_i^{(t)}) \quad (2\text{-}5)$$

Where $v_i^{(t)}$ represents the velocity of particle i at time t, w is the inertia weight, which controls the magnitude of velocity changes. c_1 and c_2 are learning factors. r_1 and r_2 are random numbers within the range [0,1]. $p_{best,i}$ is the best position found so far by particle i. g_{best} is the best position found by the all swarm.

In this study, to fully consider the impact of buildings on gas diffusion in real environments, a plume dispersion model was specifically used to simulate the gas diffusion at leak-prone parts such as bends and flanges in gas pipelines. Using the PDE toolbox in MATLAB, we successfully built a detailed two-dimensional partial differential equation (PDE) model. Various coefficients were set for the PDE equation, and the equation was solved by generating a mesh. The key role of this model is that it can verify whether the selected sensor layout can detect a specific concentration of gas within a set time. If some sensors at certain locations do not meet this requirement, the algorithm will re-optimize until the most suitable sensor layout is found.

Through precise algorithm training and validation, we finally obtained the sensor placement matrix H. Notably, a coverage of 97% was achieved after just 10 iterations, demonstrating the high efficiency of this research method. Particularly, comparison graphs between the Greedy & PSO method (combined Greedy algorithm and PSO) and the sole PSO method showed that not only did the combined method accelerate the speed of coverage improvement, but it also quickly reached a high coverage rate in the early iterations, showing a significant advantage. The Greedy & PSO curve has a steeper slope in the initial iterations, indicating a faster rate of coverage growth. In contrast, the slope of the PSO algorithm's curve is smaller, showing a slower rate of coverage growth. However, as the number of iterations increases, the coverage rates of the two methods tend to converge, illustrating the efficiency advantage of the combined algorithm in the early iterations. In the comparison between Greedy & PSO and the SA algorithm, Greedy & PSO rapidly achieved a 97% coverage rate after about 10 iterations, while the growth of the SA algorithm's coverage rate was relatively slow. This rapid growth in the early iterations highlights the efficiency of the combined algorithm in the early optimization process and its significant advantage in quickly achieving high coverage rates. Additionally, the floor plan demonstrates the practical application of the algorithm in spatial layouts, where sensor positions are evenly distributed at key monitoring points to adapt to the building layout's influence on gas diffusion. This layout optimization not only improves monitoring efficiency but also emphasizes the algorithm's adaptability and effectiveness in handling complex constraints in the real world.

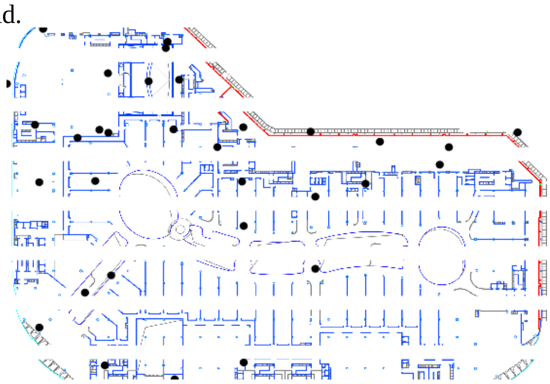

Figure 2-2. Diagram of Sensor Placement Results

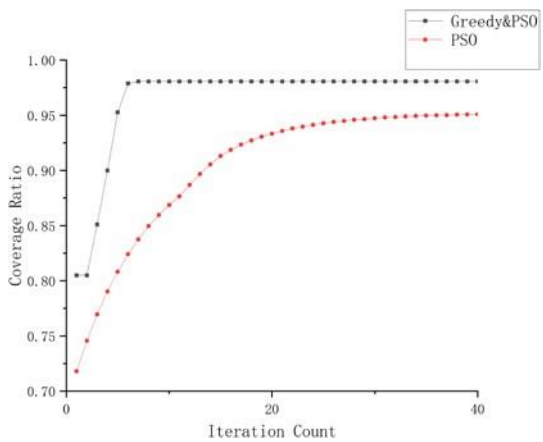

Figure2-3. Algorithm Optimization Comparison Chart

3. RESULTS AND DISCUSSION

In this study, a detailed computational fluid dynamics (CFD) simulation was conducted for one of the 64 segmented small areas to analyse the leakage process within a specific region. This area, due to its complex piping configuration including bends, flanges, and joints, has multiple potential leakage points, making it the focus of the simulation analysis, Ansys simulation is used to verifies the accuracy of the sensor optimization results.

Under the simulation conditions, the pressure of the gas pipeline in the commercial complex is set at 10 MPa, assuming that the leakage occurs at the position of a bend, with a leak area of 1 cm^2.

The CFD simulation setup reflects the actual scenario where the leak point is directed indoors to simulate the process of gas leakage spraying into a building. The Species Transport model used in the simulation accurately analyses the mixture components of methane gas and air. The SIMPLEC solver method, along with the settings for the time step and number of iterations, ensures the precision and stability of the simulation solution.

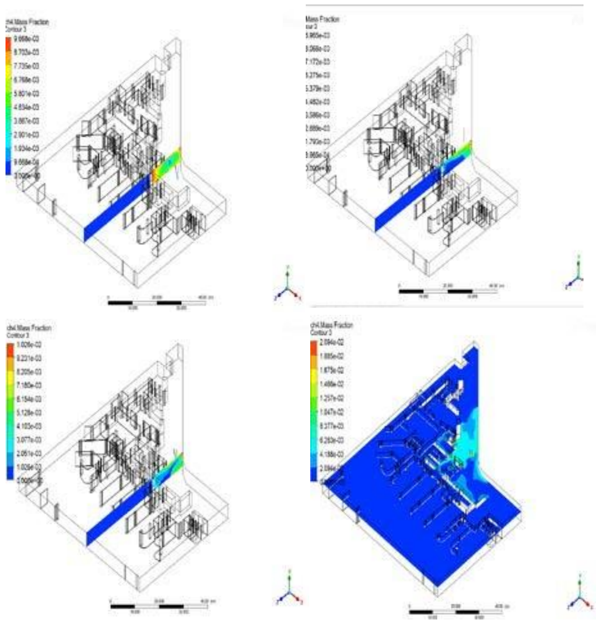

Figure 2-3 Simulation Results Graph

By placing sensors in key areas, we monitored the methane concentration components. When the methane concentration detected by the catalytic combustion sensor reaches 20% LEL (Lower Explosive Limit), the sensor will trigger an alarm. According to the simulation results, the monitoring data under the original sensor arrangement showed that not all leak points could reach this set threshold. With the optimized layout, we observed that the concentration curves at all leak points rose to or exceeded the standard of 0.002 within 100 seconds. This rapid response time provides ample margin for action within the emergency handling window (set at 3 minutes), thereby confirming the effectiveness of the sensor layout optimization. Moreover, the concentration curves showed a stable or declining trend after reaching the threshold, suggesting improvements in data stability with the optimized system.

In summary, the optimization of algorithms has significantly enhanced the monitoring capability of the gas leakage detection system and improved the system's efficiency in issuing warnings at critical moments. This progress not only demonstrates the value of combining computational fluid dynamics with algorithmic optimization in practical applications but also lays a solid foundation for further research in this field.

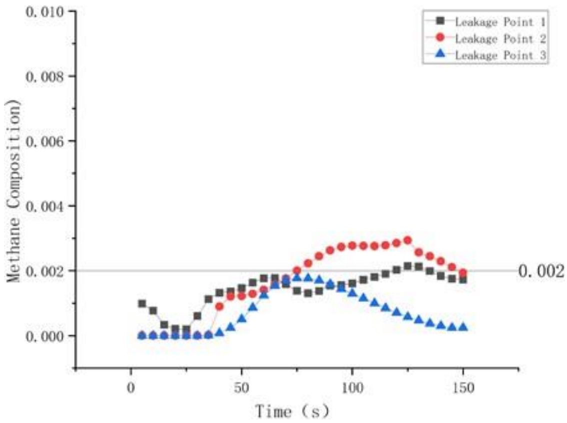

Figure 2-4 Original Methane Composition Graph of Sensor

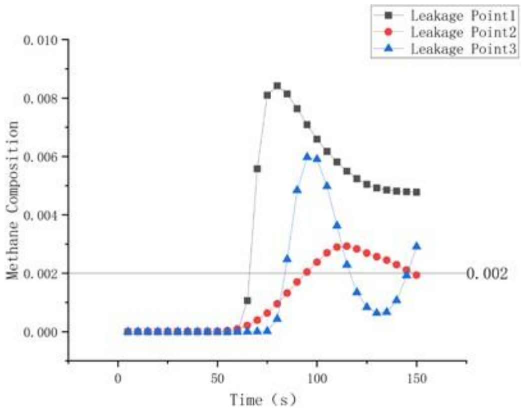

Figure 2-5 New Methane Composition Graph of Sensor

4. CONCLUSIONS

This study integrates greedy algorithms and PSO with CFD simulations to successfully optimize the layout of indoor gas leak detection sensors. The optimization considers the complex spatial structures and gas diffusion paths in commercial areas, as well as the need for rapid detection in emergency situations. Through precise simulation processes, the optimal placement of sensors in key areas was determined to trigger alarms promptly in the event of a leak.

Simulation results show that the optimized sensor layout can detect methane concentrations exceeding 20% LEL (Lower Explosive Limit) at all potential leak points within 100 seconds, significantly outperforming the original layout. This response time meets the set requirement for emergency handling within three minutes and ensures the data collected are highly stable and reliable. Moreover, the optimization of sensor placement reflects a thorough understanding of the convection-diffusion process and a deep grasp of environmental characteristics and safety requirements.

The application of the combined algorithm and CFD simulation results not only enhances the performance of the gas leak detection system but also provides an effective safety monitoring solution for commercial areas. Future research should expand to different scales and complexities of environments to further verify the applicability and resilience of the algorithm. Additionally, improvements to the algorithm itself, such as introducing more advanced optimization mechanisms, will further enhance the performance of the sensor network, thereby ensuring public safety in a broader range of applications.

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