

A data-driven algorithm to optimize the placement of continuous monitoring sensors on oil and gas sites

Meng Jia, Troy Sorensen, Will Daniels,
Dorit Hammerling
Applied Mathematics and Statistics
Colorado School of Mines

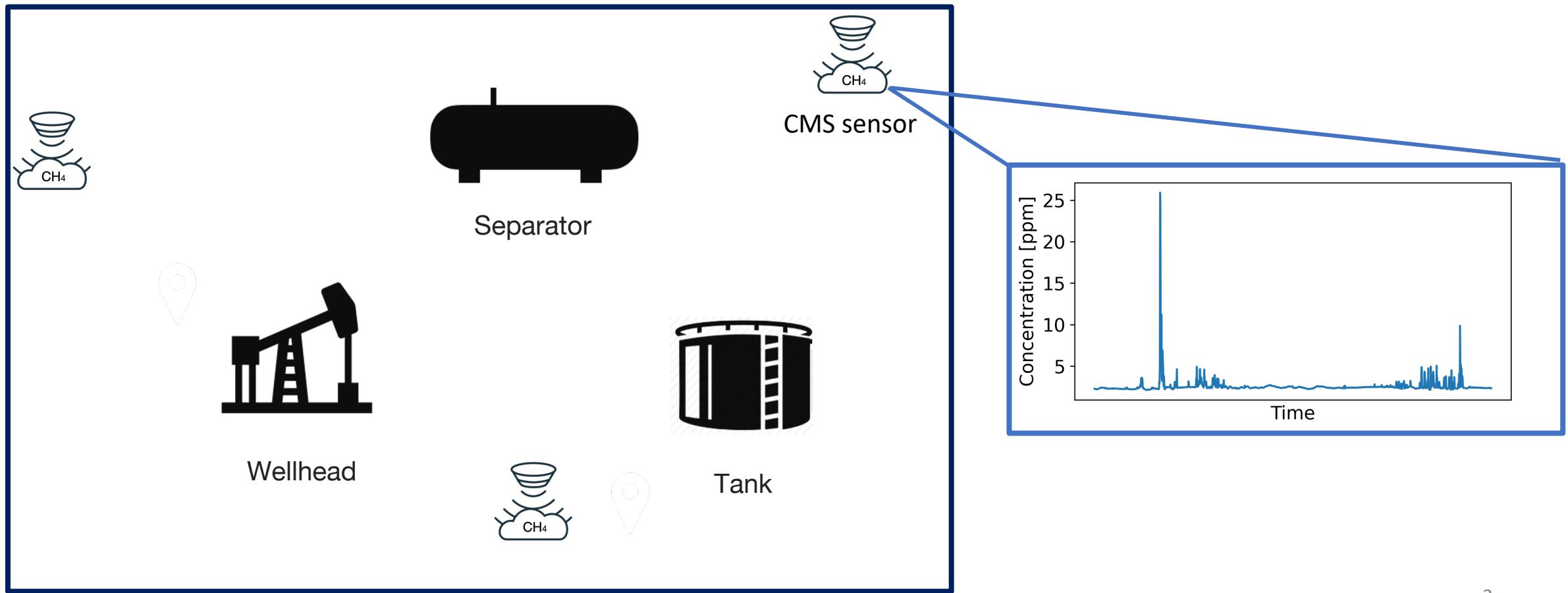


AGU23
San Francisco, CA & Online Everywhere
11-15 December 2023

December 11, 2023,
San Francisco, CA

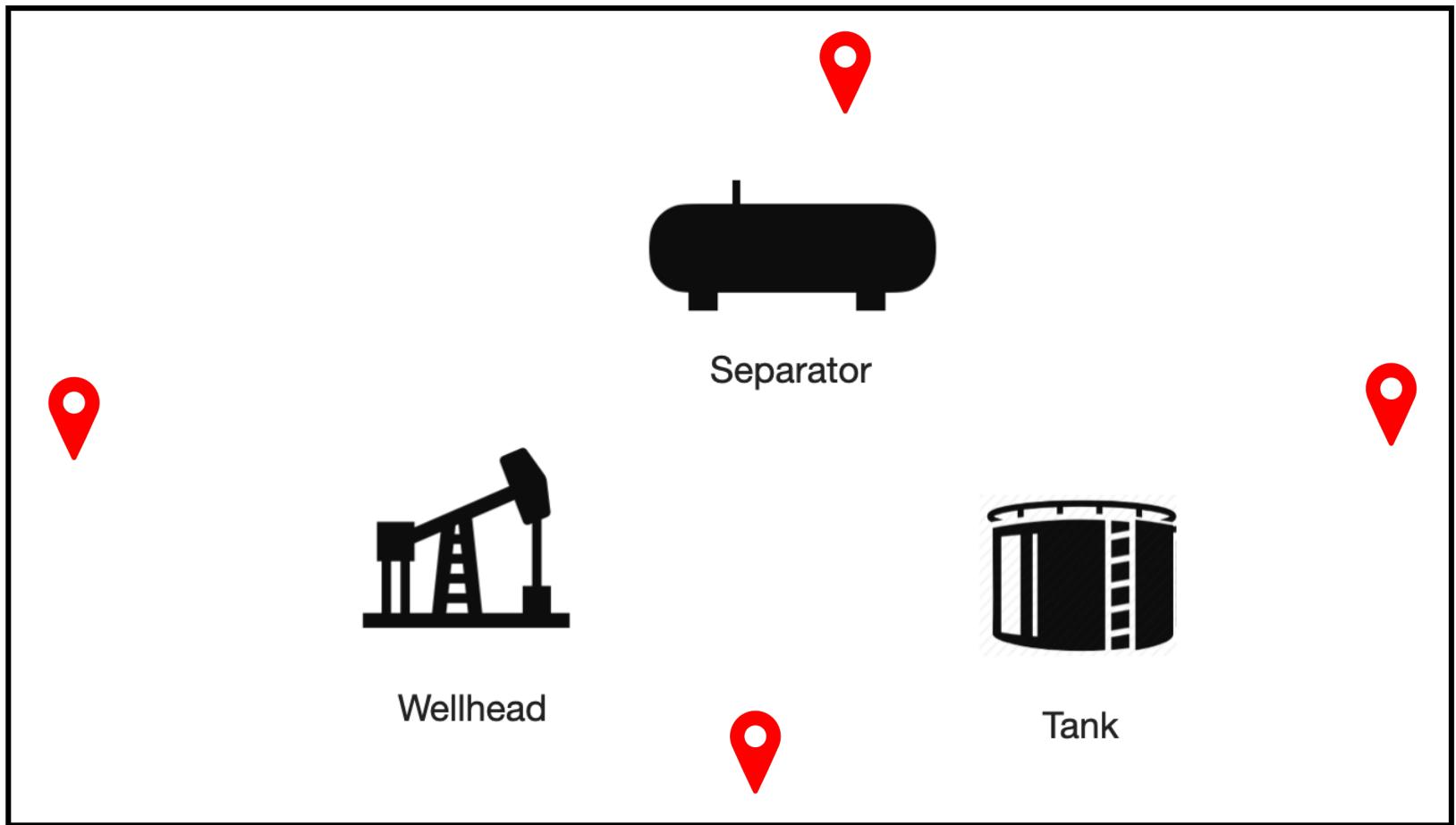
Problem Setup

- Continuous monitoring systems (CMS)



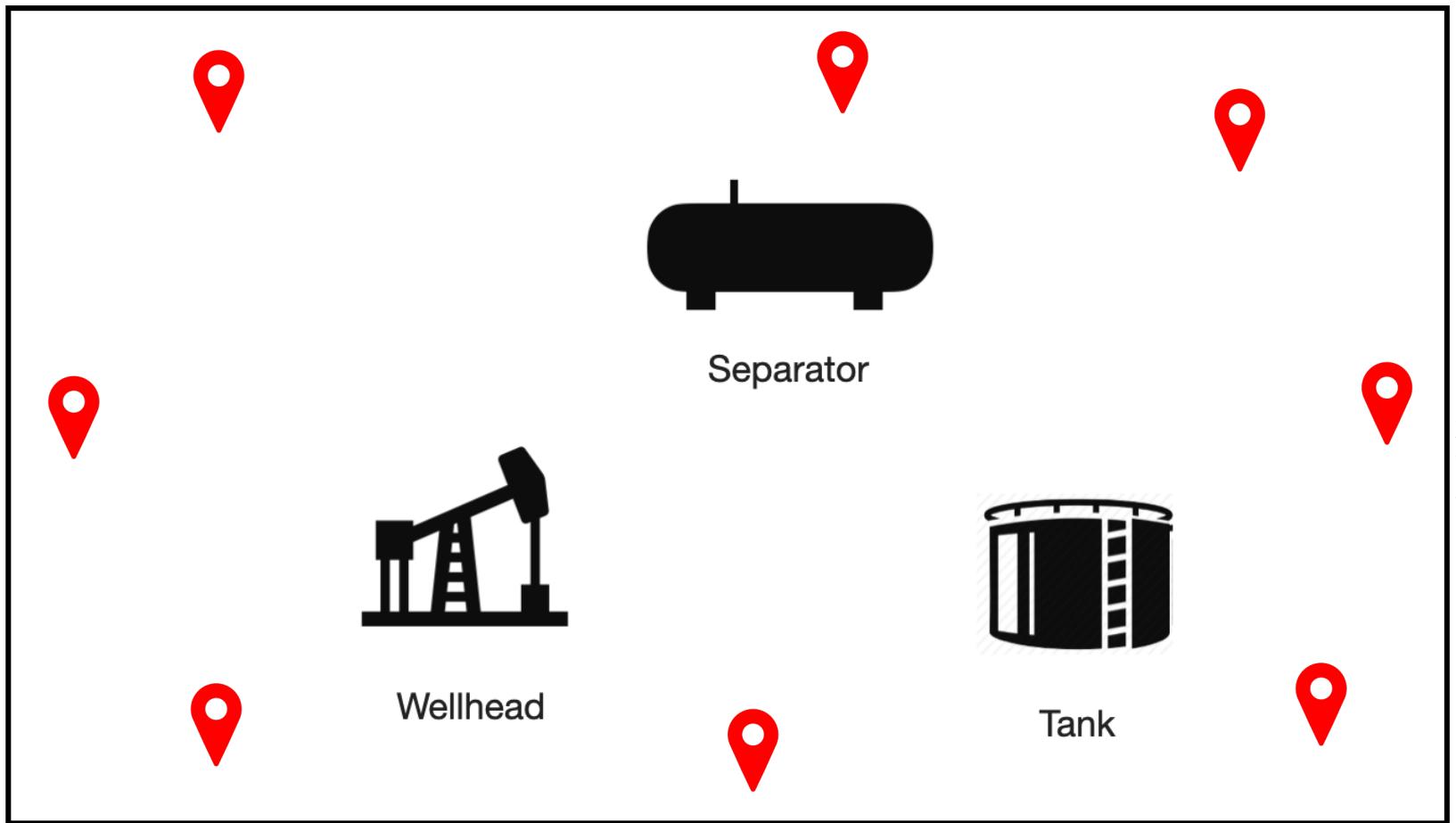
Problem Setup

- CMS sensor placement



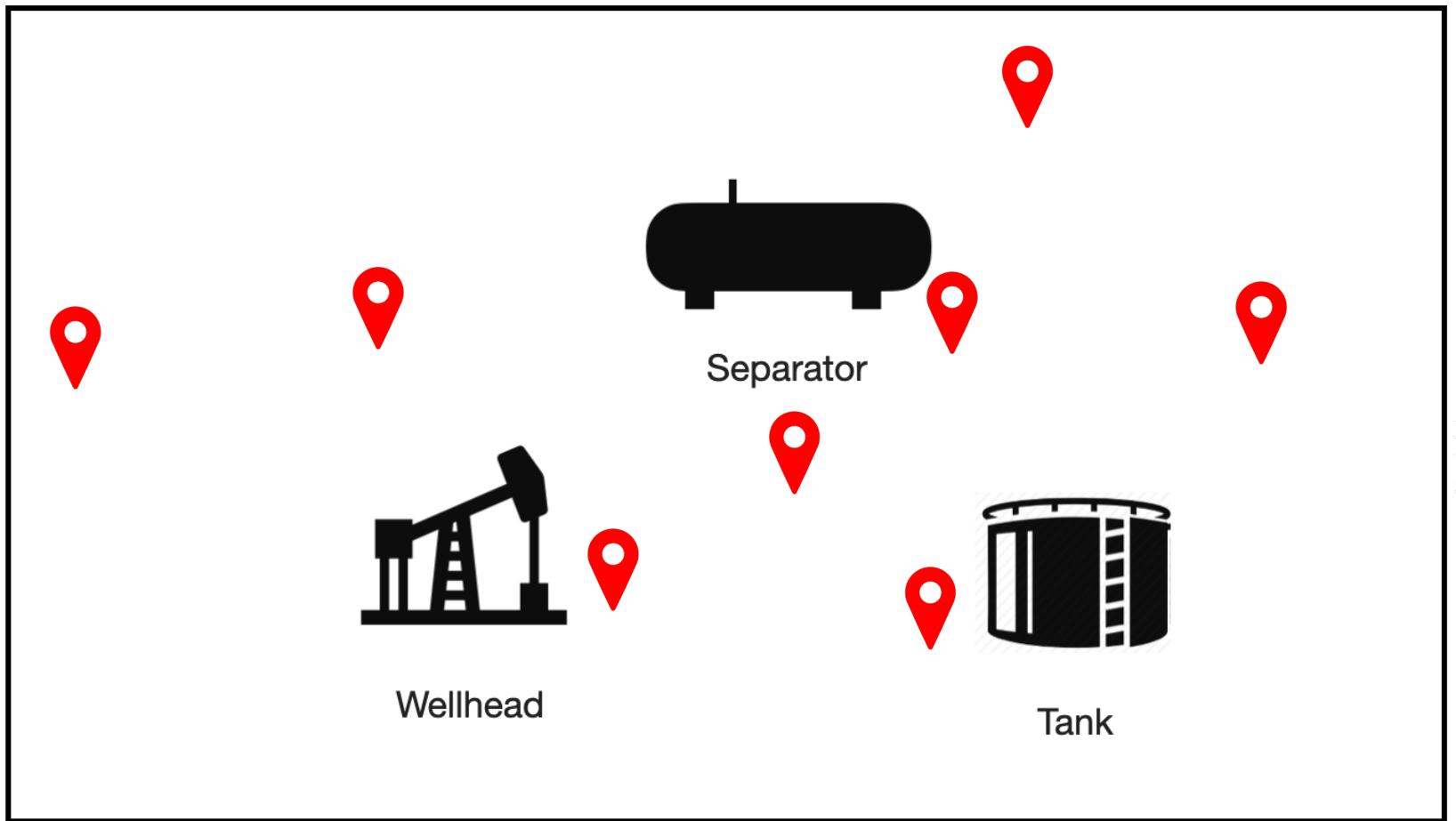
Problem Setup

- CMS sensor placement



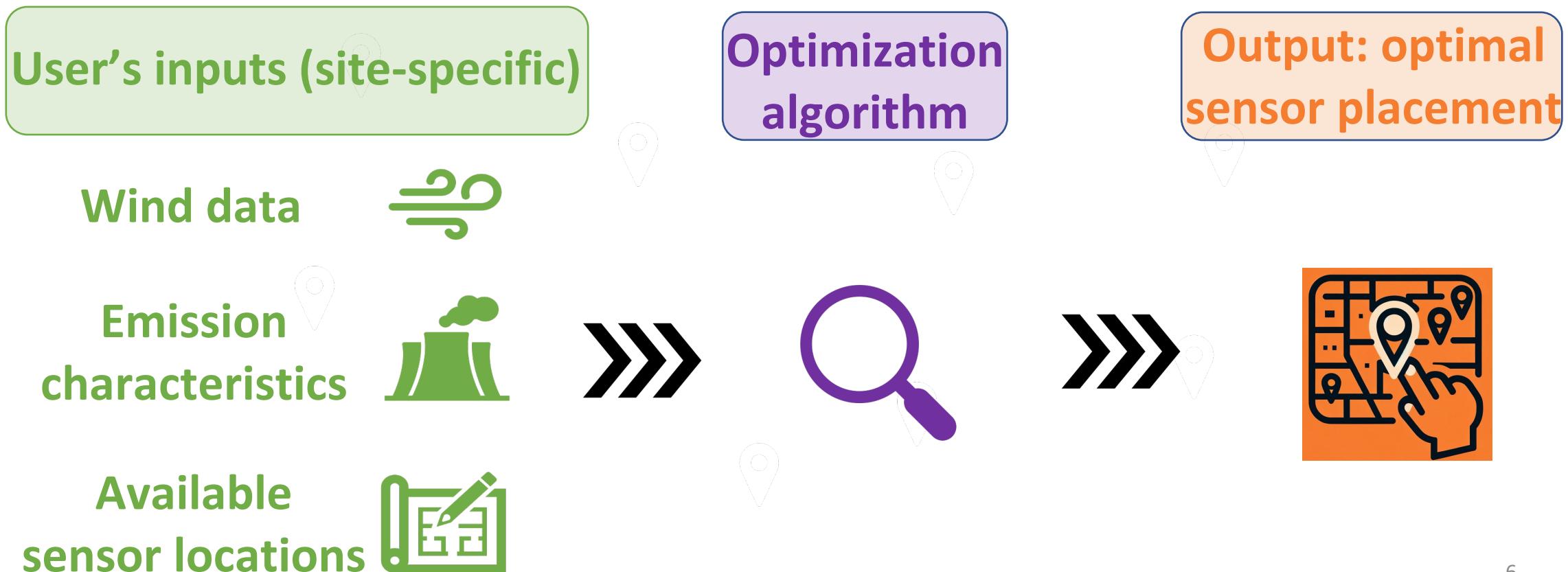
Problem Setup

- CMS sensor placement

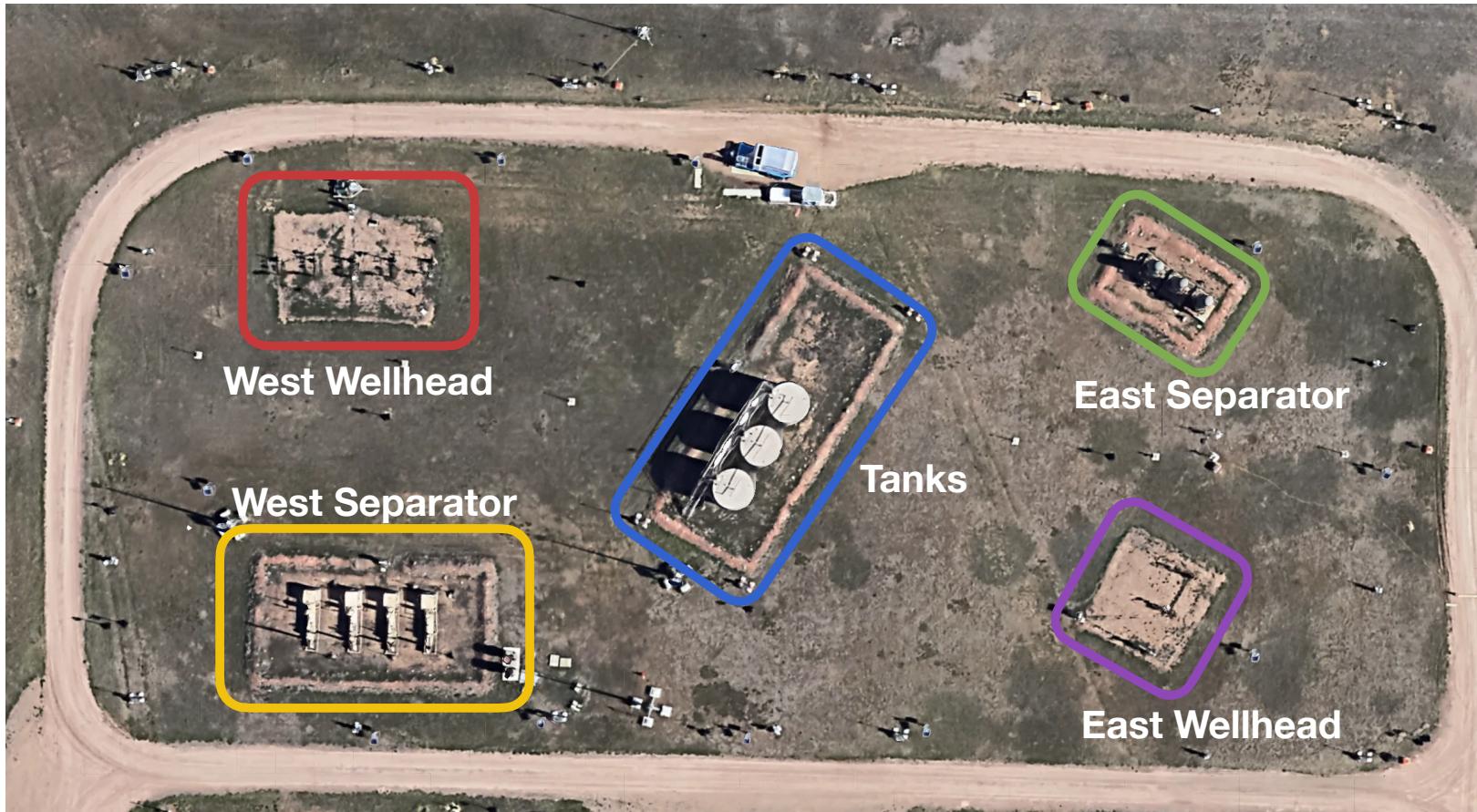


Problem Setup

- A data-driven algorithm to optimize sensor placement for best emission detection



Experiment Data



METEC Facility, 5 potential emission sources

Algorithm

1

Generate emission scenarios

2

Set possible sensor locations

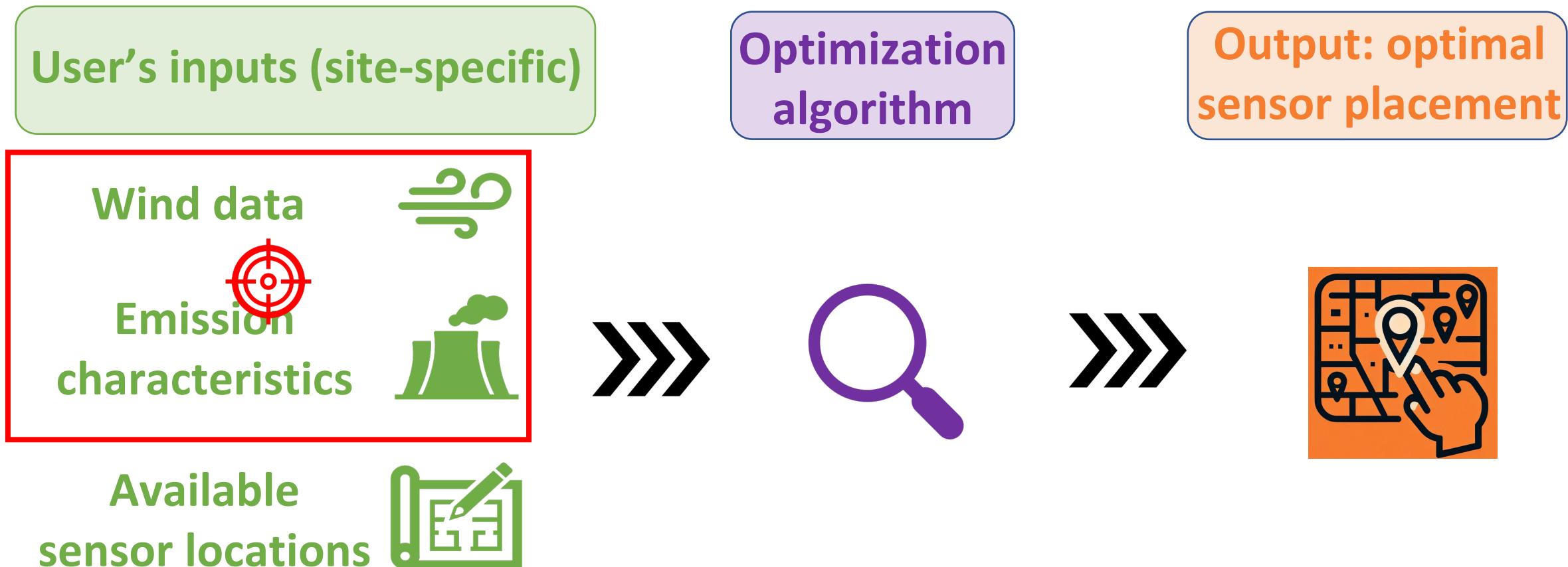
3

Simulate concentrations & Check detection

4

Optimize sensor placement

Step 1 Generate Emission Scenarios

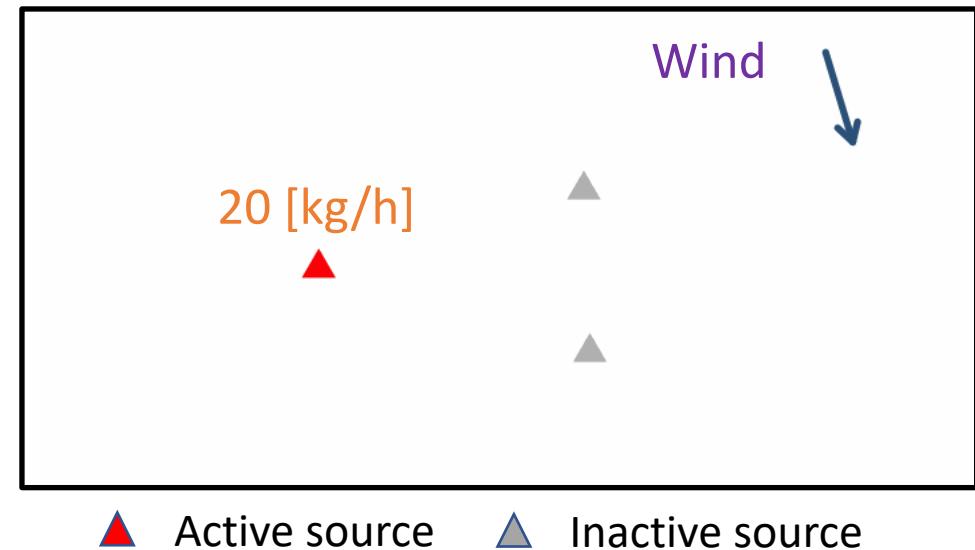


Step 1 Generate Emission Scenarios

A combination of

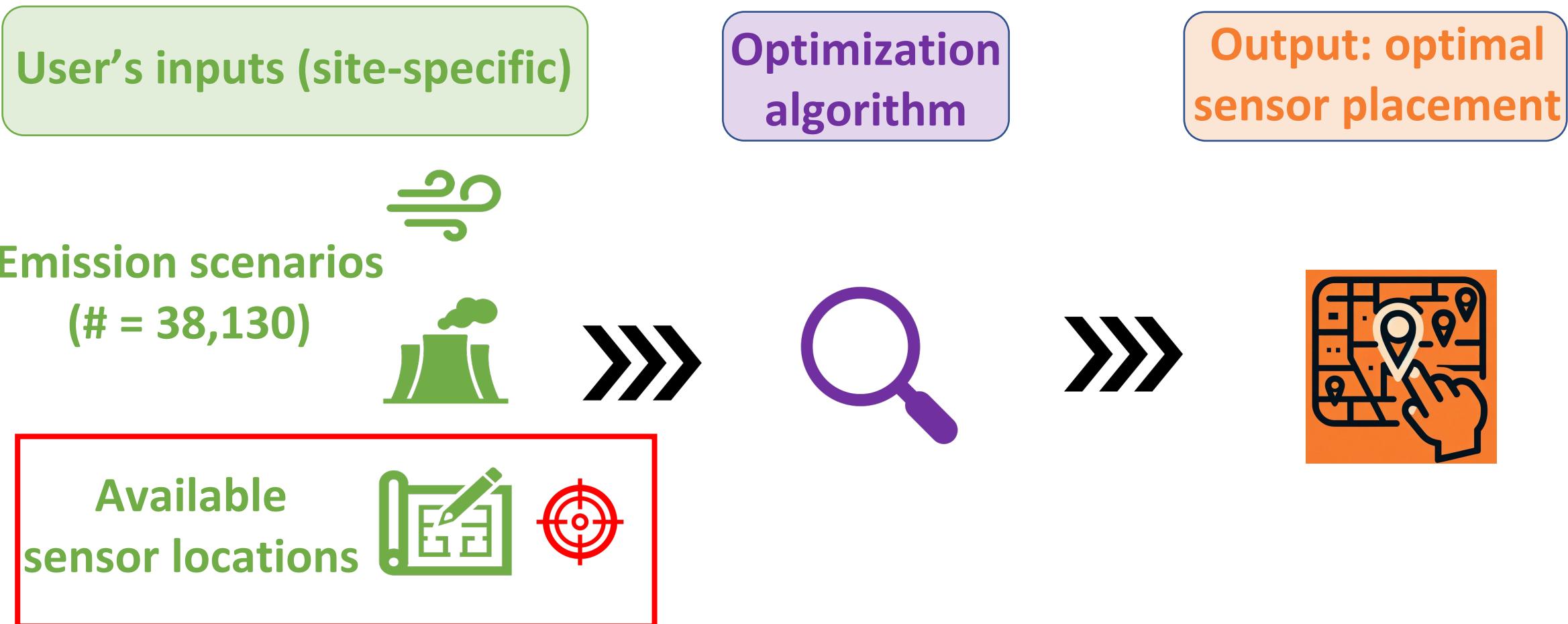
- wind speed time series
- wind direction time series
- emission source location
- emission rate

defines an emission scenario.

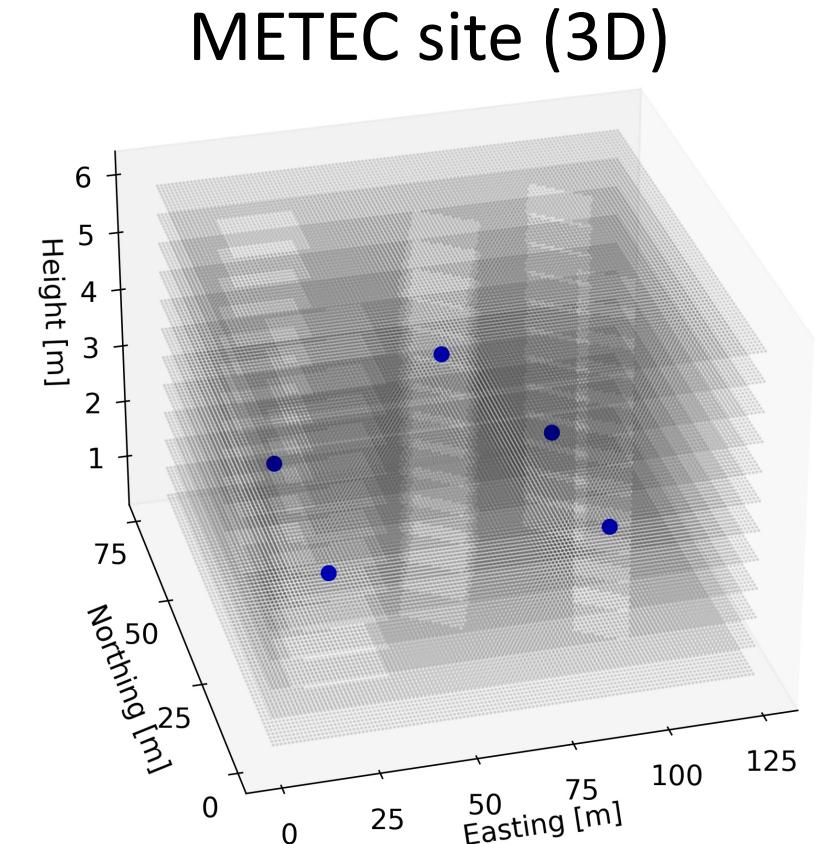
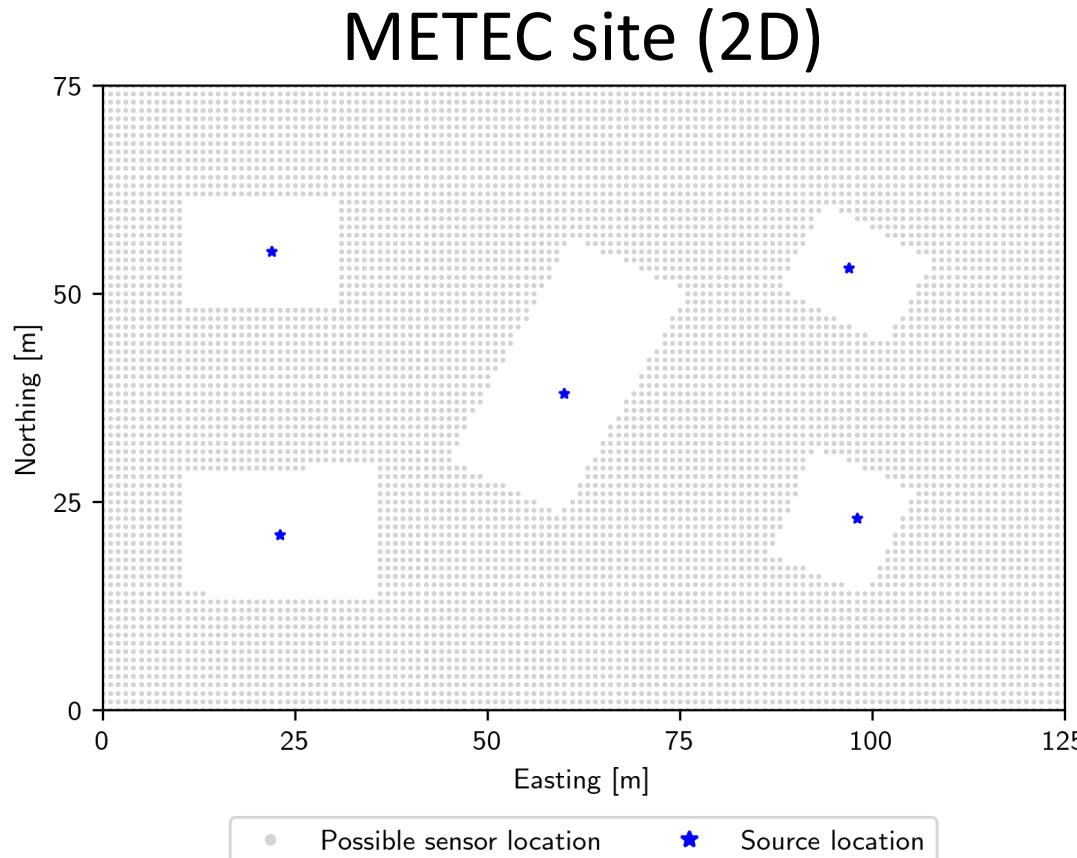


- Estimate probability distributions of wind & emission to sample → 38,130 emission scenarios

Step 2 Set Possible Sensor Locations



Step 2 Possible Sensor Locations



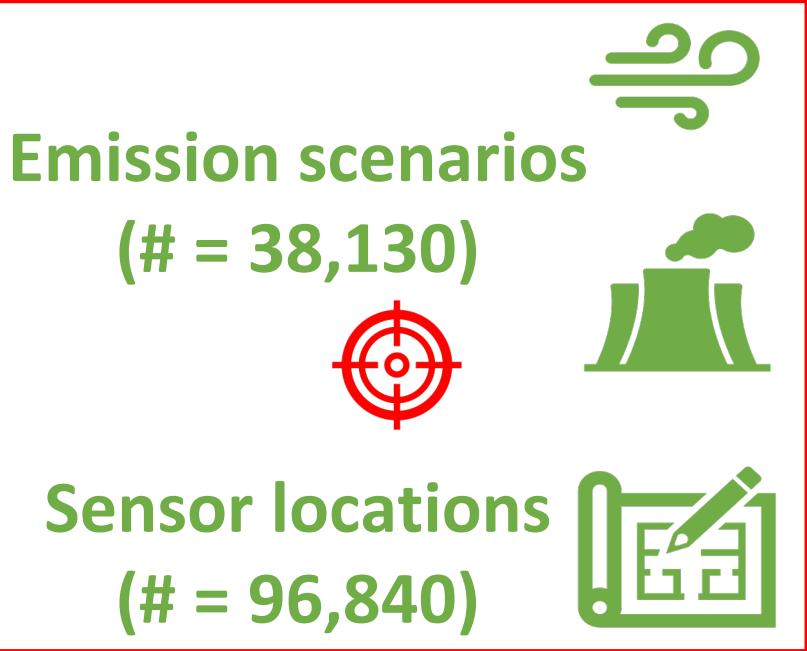
resolution = 1 m for Northing & Easting; = 0.5 m for vertical
possible locations = 96,840

Step 3 Concentration Simulation & Detection

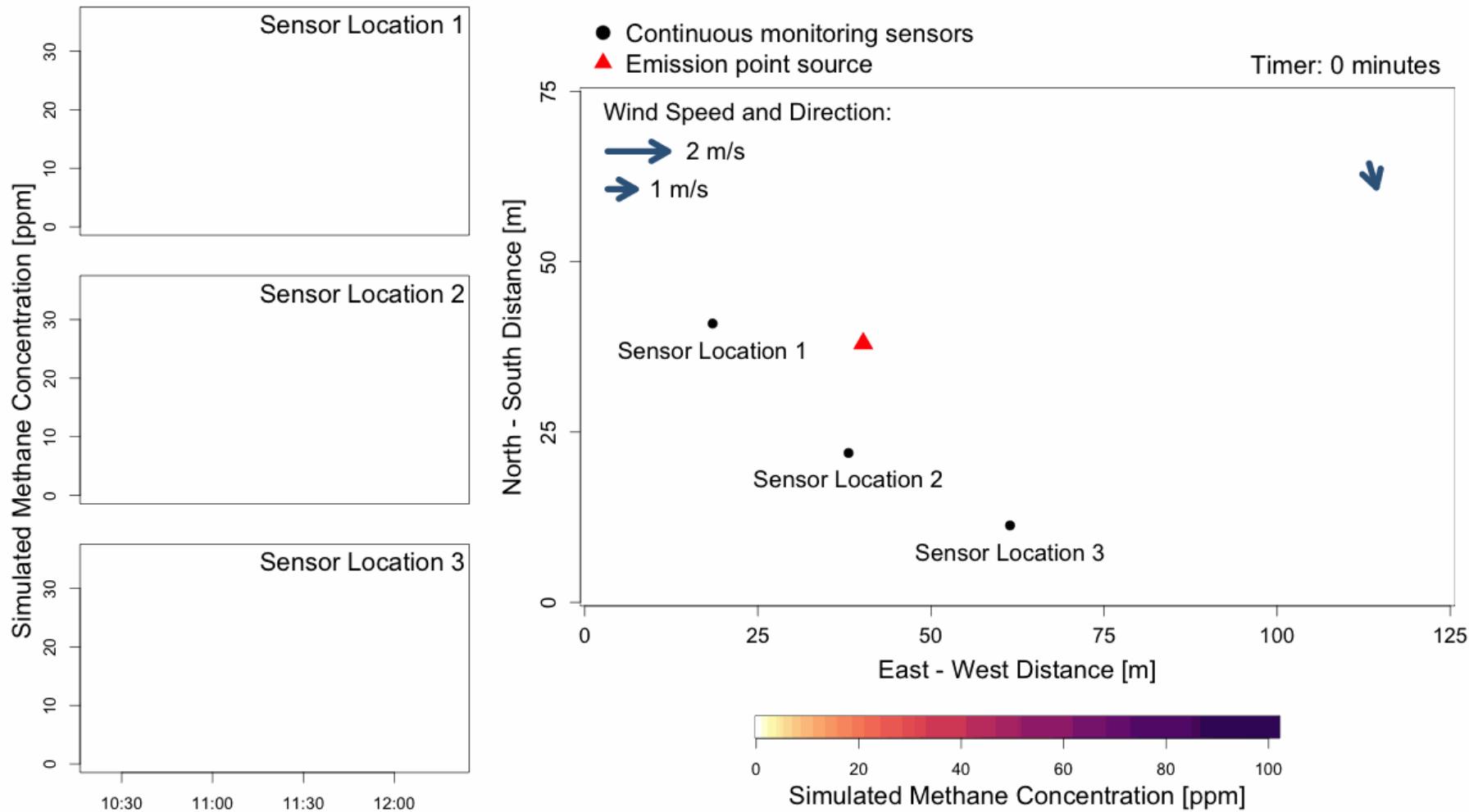
User's inputs (site-specific)

Optimization algorithm

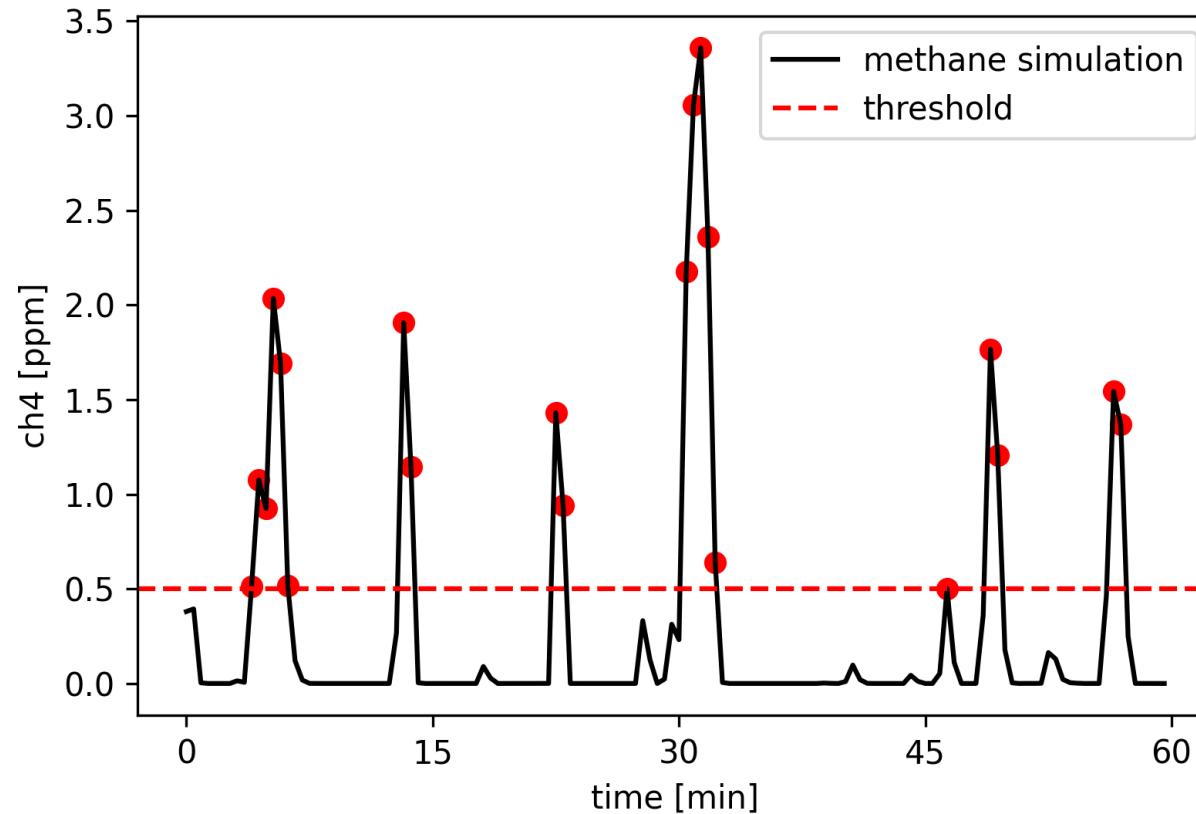
Output: optimal sensor placement



Step 3.1 Gaussian puff simulation

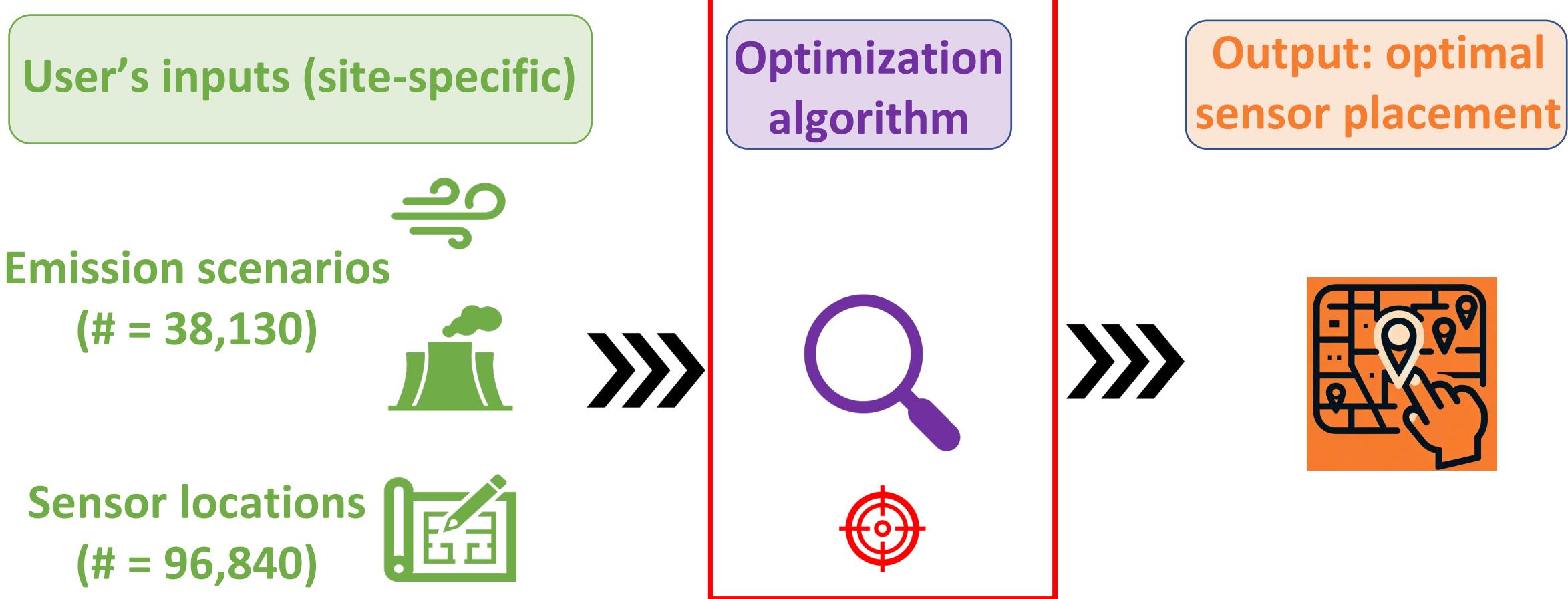


Step 3.2 Detection



Example of simulated concentrations and detection for
Emission Scenario j at Sensor Location i

Step 4 Optimize Sensor Placement



Step 4 Optimization

Rows of D : Sensor Locations (SL)

Cols of D : Emission Scenarios (ES)

$D_{ij} = 0$, if SL_i can detect ES_j;

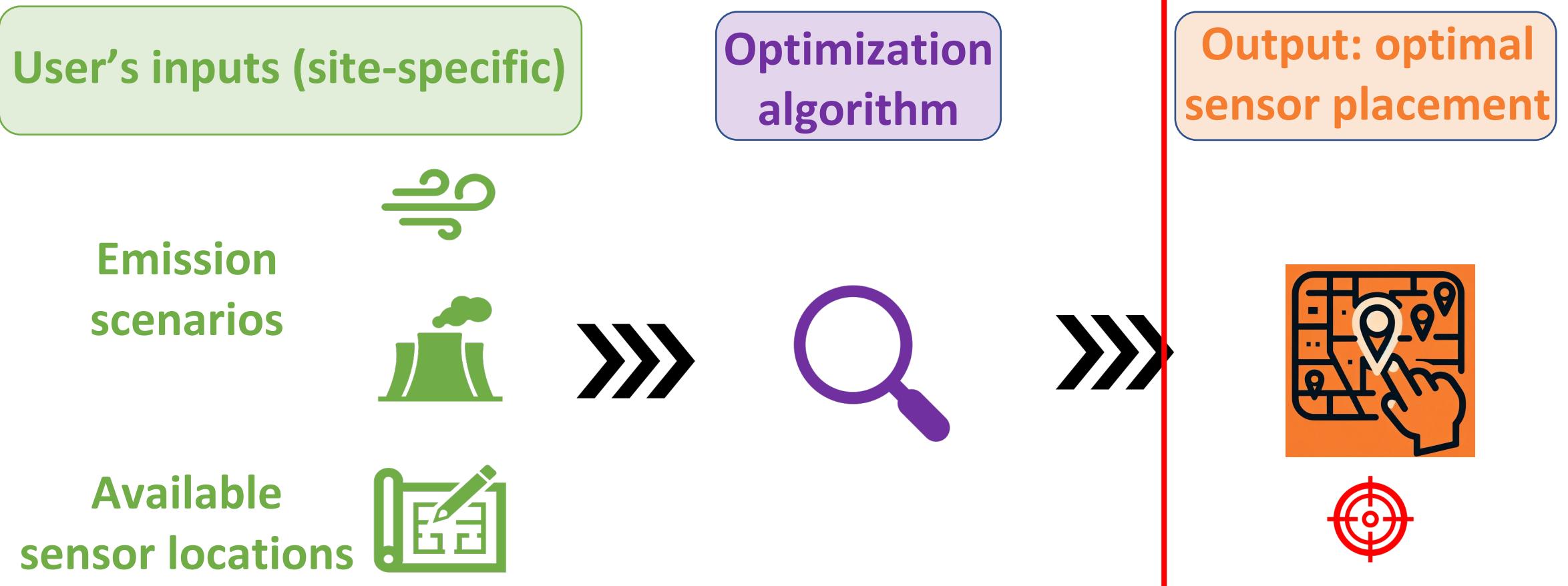
$D_{ij} = 1$, otherwise

Evolutionary Algorithms
+
Pareto Optimization

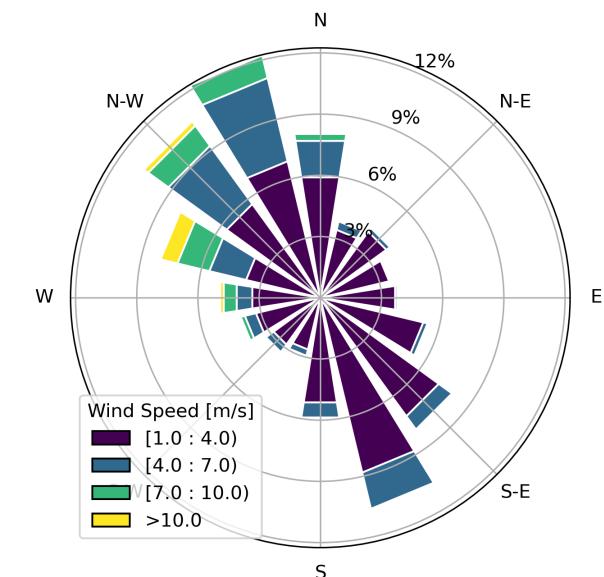
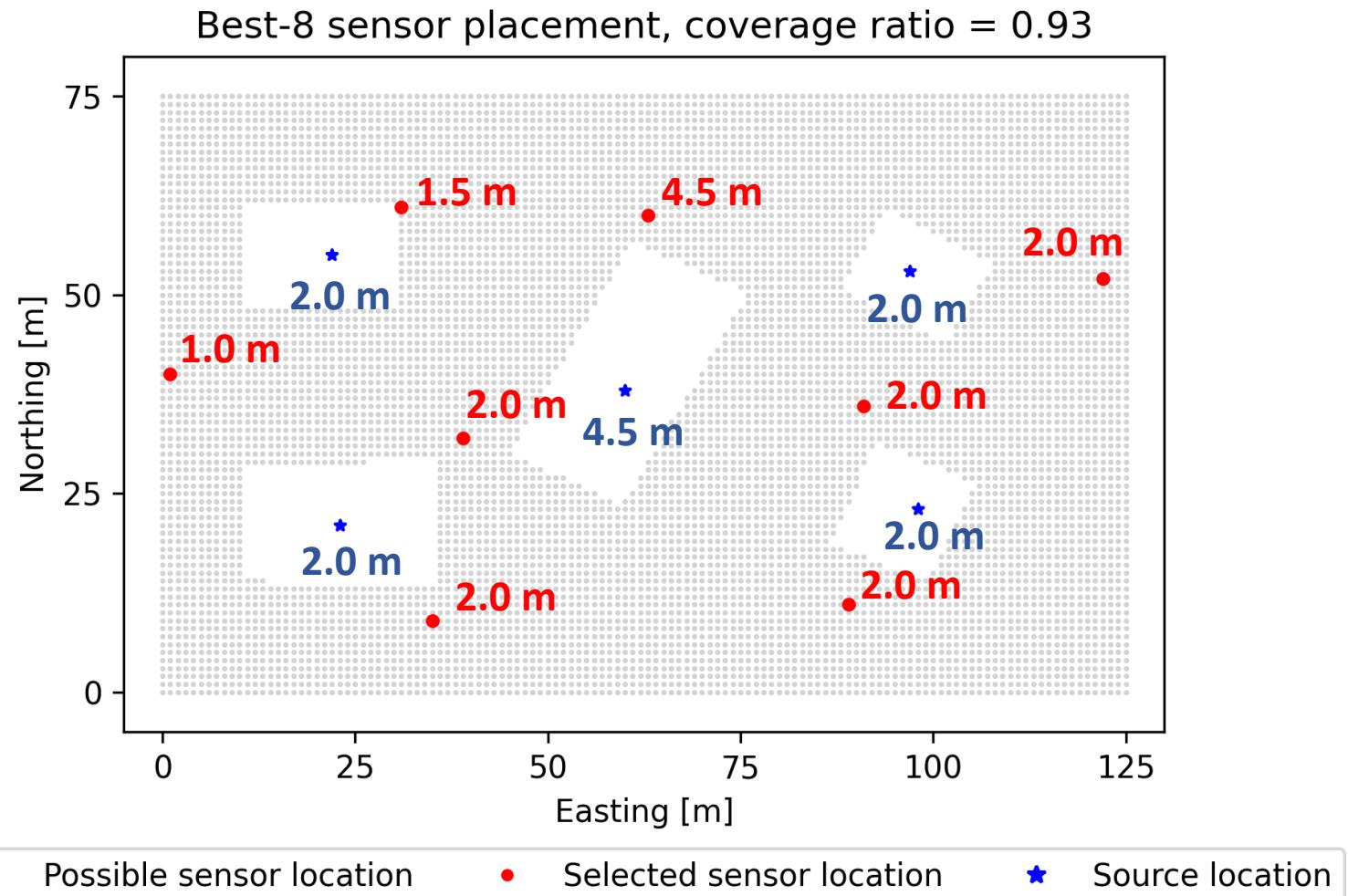
	ES ₁	ES ₂	...	ES _j	...	ES _M
SL ₁	1	1	...	0	...	1
SL ₂	1	0	...	0	...	1
:	:	:	⋮	⋮	⋮	⋮
SL _i	0	0	...	1	...	1
:	:	:	⋮	⋮	⋮	⋮
SL _N	1	1	...	1	...	1

Detection Matrix D
 $N = 96,840; M = 38,130$

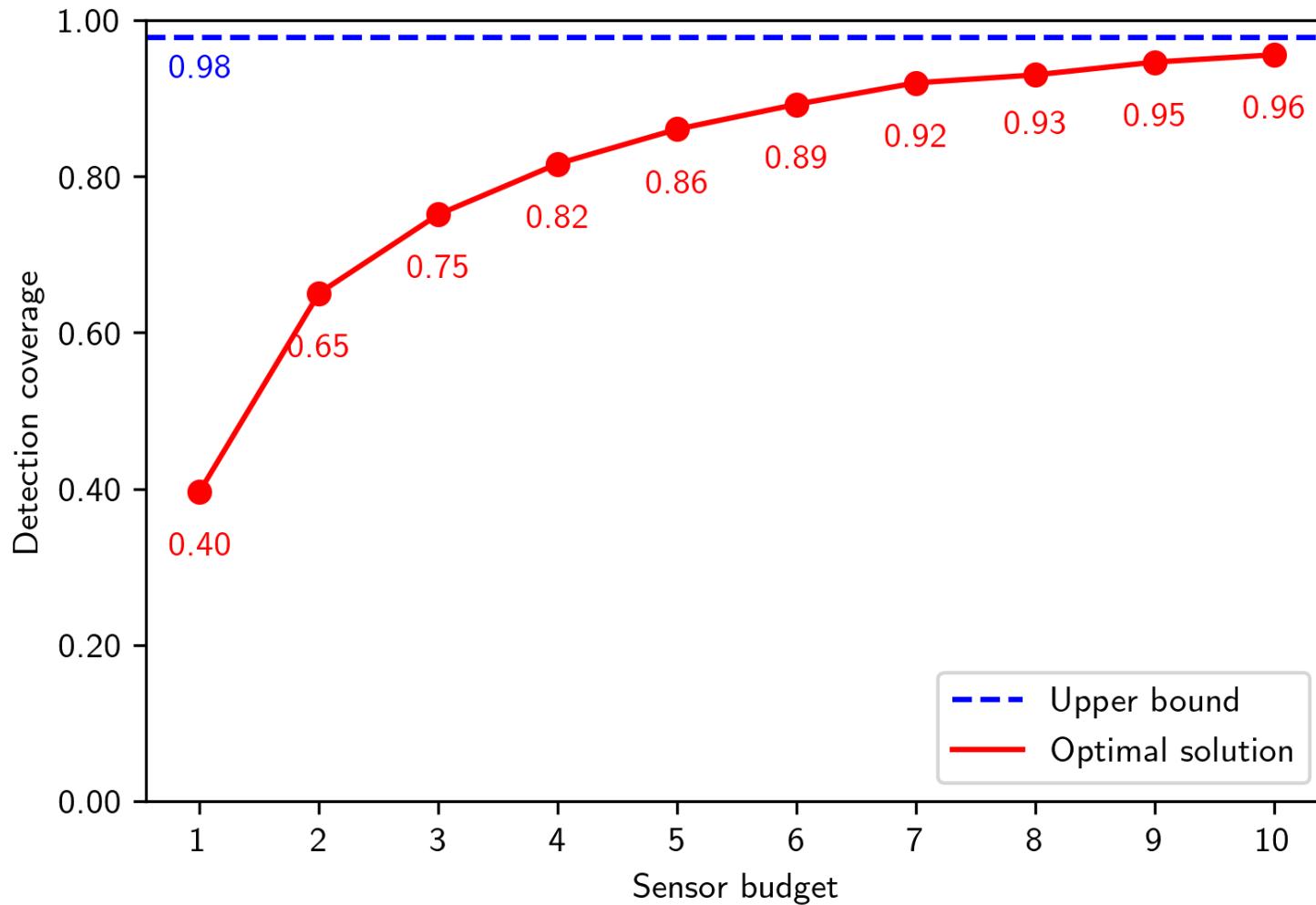
Results



Results: Best 8-sensor placement



Results: Budget vs. coverage



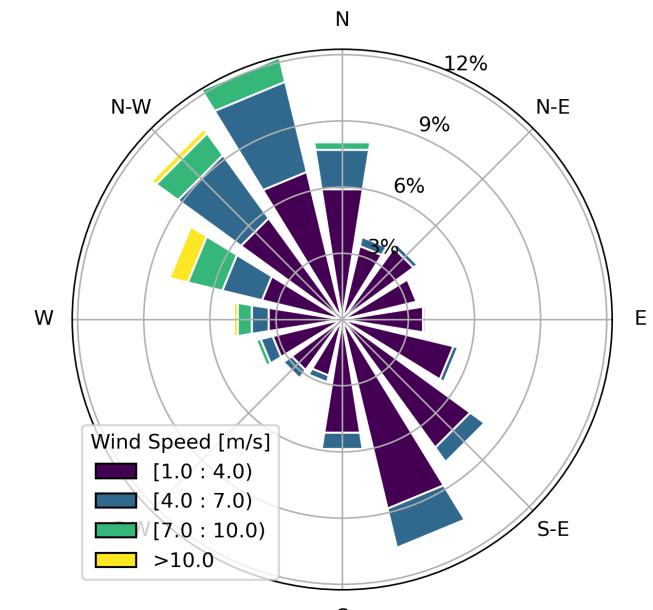
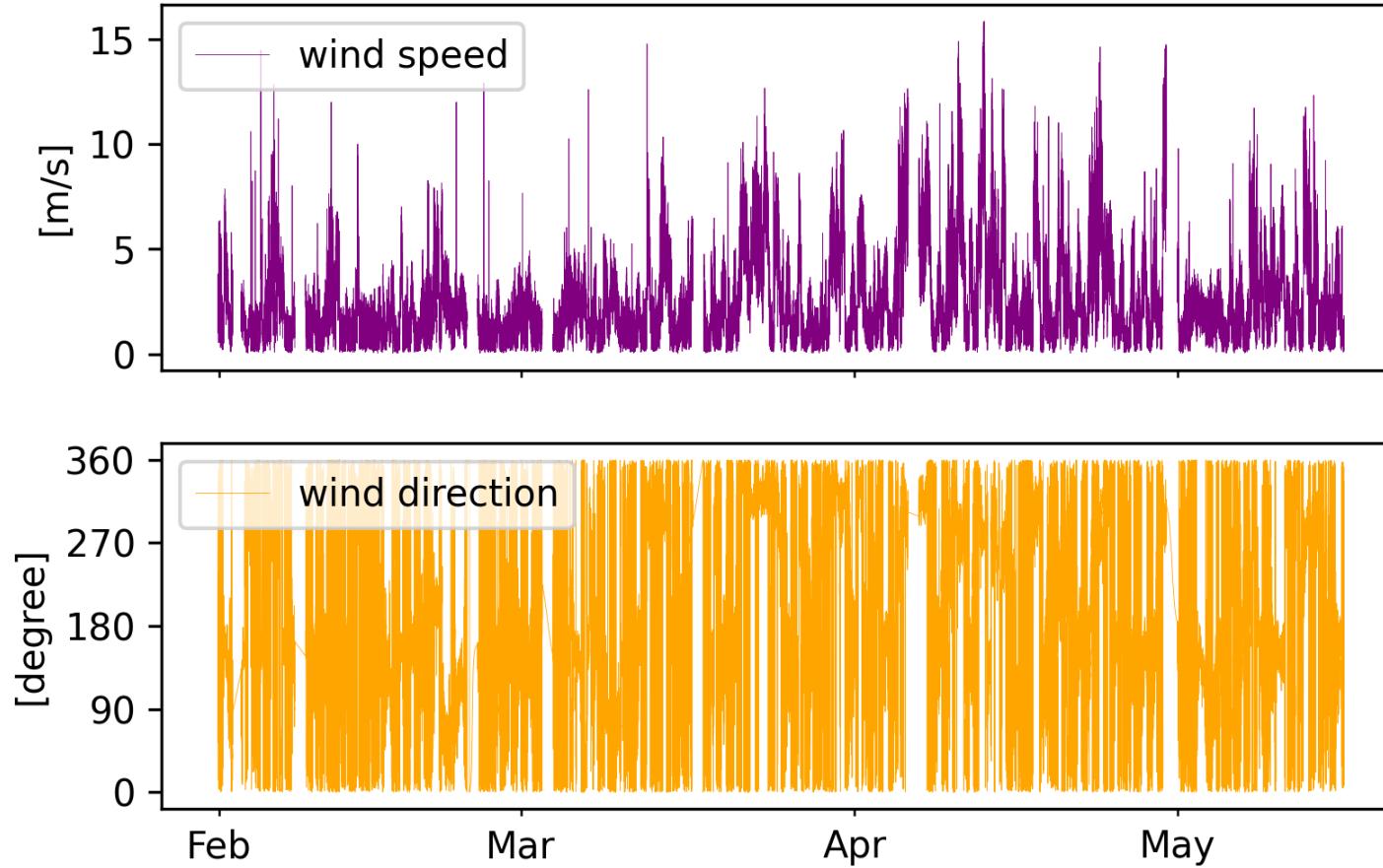
Thank you for
attending!
Questions?



Visit my iPoster
for more details!

Back up

Experiment Data



Wind Data on METEC, February through May 2022

Step 4.2 Pareto Optimization & EA

Pareto Optimization

Objectives:

Find a subset of rows (a solution) from the detection matrix to

- maximize emission scenario coverage.
- minimize the size of the subset.

Exhaustive search and standard linear programming algorithms are impossible for large-scale problem!

Evolutionary Algorithms

Process:

1. Randomly initialize a population of solutions.
2. Propose new solutions by perturbing existing solutions.
3. Update the population by eliminating worse solutions.
4. Repeat Step 2 & 3 until converge.
5. Return the best k -size solution.

Conclusions & Future Work

- Developed a data-driven algorithm for sensor placement more accurate and efficient than traditional methods.
- The algorithm's modularity ensures adaptability to various monitoring needs.
- Optimized for solving large-scale problems efficiently.
- To implement a generative model for better approximation of wind distributions, thereby expanding the emission scenario database.
- To investigate advanced data embedding techniques to manage and solve problems of greater scale.

References

- Klise, Katherine A., et al. "Sensor placement optimization software applied to site-scale methane-emissions monitoring." *Journal of Environmental Engineering* 146.7 (2020): 04020054.
- Qian, Chao, Chao Bian, and Chao Feng. "Subset selection by pareto optimization with recombination." *Proceedings of the AAAI Conference on Artificial Intelligence*. Vol. 34. No. 03. 2020.

Close sensor locations

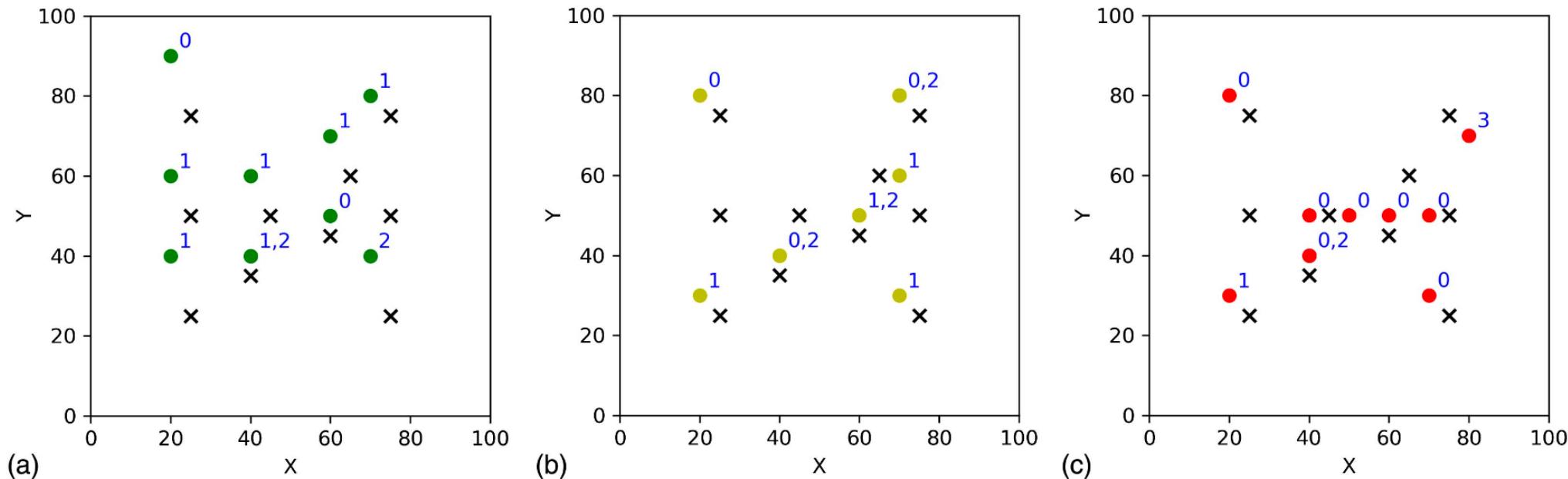
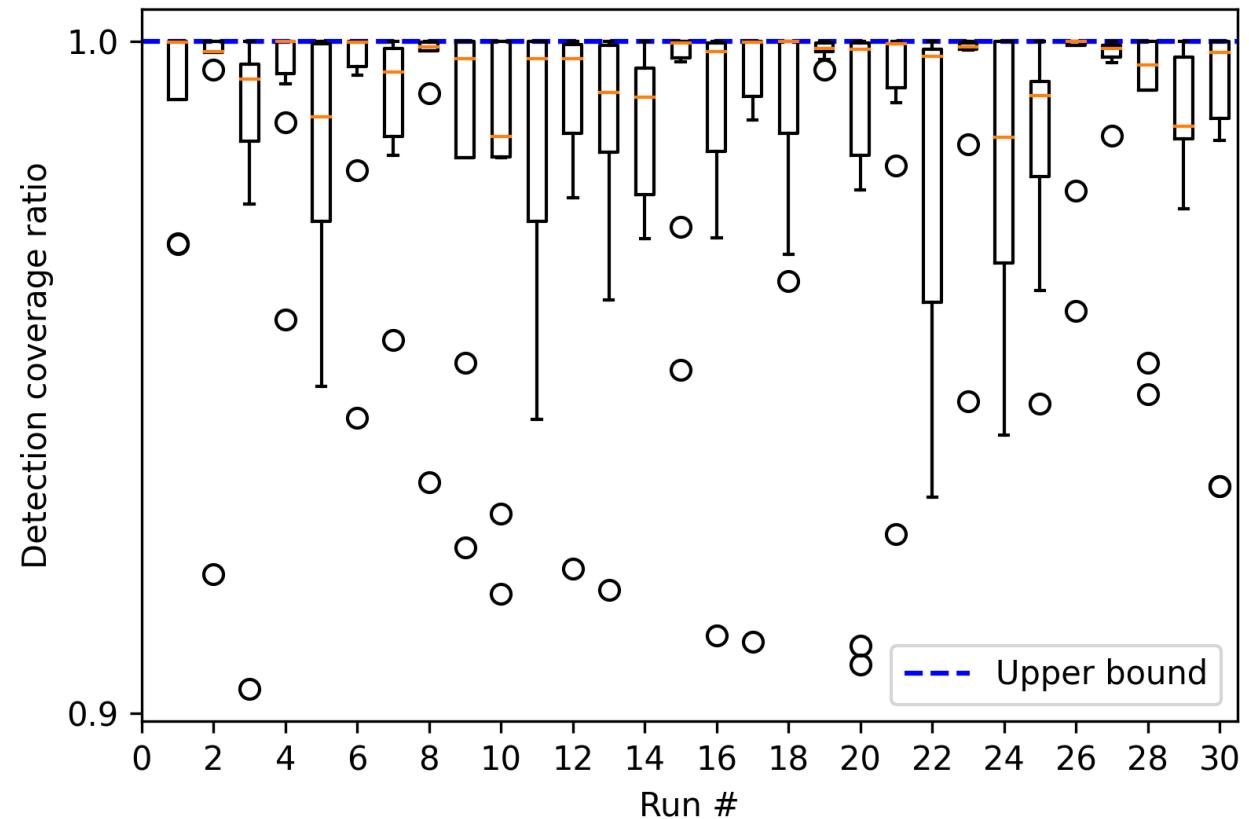


Fig. 9. Optimal sensor placements with 10 sensors maximizing scenario coverage considering (a) high-sensitivity; (b) moderate-sensitivity; and (c) low-sensitivity sensors. X's represent the potential leak locations. The height of each sensor is noted (some sensors overlap in plan-view).

Figure 9 in Klise et al. (2020)

Test EA on synthetic large matrix

- `nrows = ncols = 100,000`
- $k = 10$, randomly placement in the big matrix
- Test on 30 cases and run 10 EA algorithm for each case



Optimality Guarantee

- In theory, we prove that for subset selection with monotone objective functions, PORSS can achieve the optimal polynomial-time approximation guarantee, $1 - e^\gamma$ where γ is the submodularity ratio measuring how close your objective function is to submodularity.

Related Work

	Klise et al. (2020)	Our work
# emission scenarios	1,200	$\approx 40,000$
# possible sensor locations	$\approx 2,500$	$\approx 100,000$
Forward model	Gaussian plume	Gaussian puff
Optimization algorithm	Mixed-integer linear programming	Pareto optimization using evolutionary algorithm (EA)

Pareto Optimization Algorithm

- General subset selection problem

Given all items $V = \{v_i\}, i = 1, 2, \dots, N$, an objective function g and a budget k , to find a subset of at most k items maximizing g , i.e.,

$$\operatorname{argmax}_{S \subseteq V} g(S) \text{ s.t. } |S| \leq k$$

- In our case, V is the set of rows of the detection matrix D
- g is the number of 0s in the column product of D^S (the k -row submatrix of D)

Pareto Optimization Algorithm

- Pareto Optimization
 - Find optimal solutions to two conflicting objectives

$$\operatorname{argmax}_{x \subseteq \{0,1\}^N} (g_1(x), g_2(x))$$

where

$$g_1(x) = \begin{cases} -\infty, & |x| \geq 2k \\ g(x), & \text{otherwise} \end{cases} \quad g_2(x) = -|x|$$

Algorithm

Input: detection matrix D ; objective function g ; budget k

Parameters: the number I of iterations

Output: a subset of k rows of D

Process:

Let $x = \{0\}^N, P = \{x\}$ and $t = 0$

While $t < T$:

Select x, y from P randomly with replacement

Apply recombination on x, y to generate x', y'

Apply bit-wise mutation on x', y' to generate x'', y''

for each $z \in \{x'', y''\}$:

if $\nexists u \in P$ such that $u > z$:

$P = (P \setminus \{u \in P | u < z\}) \cup \{z\}$

Check early stop

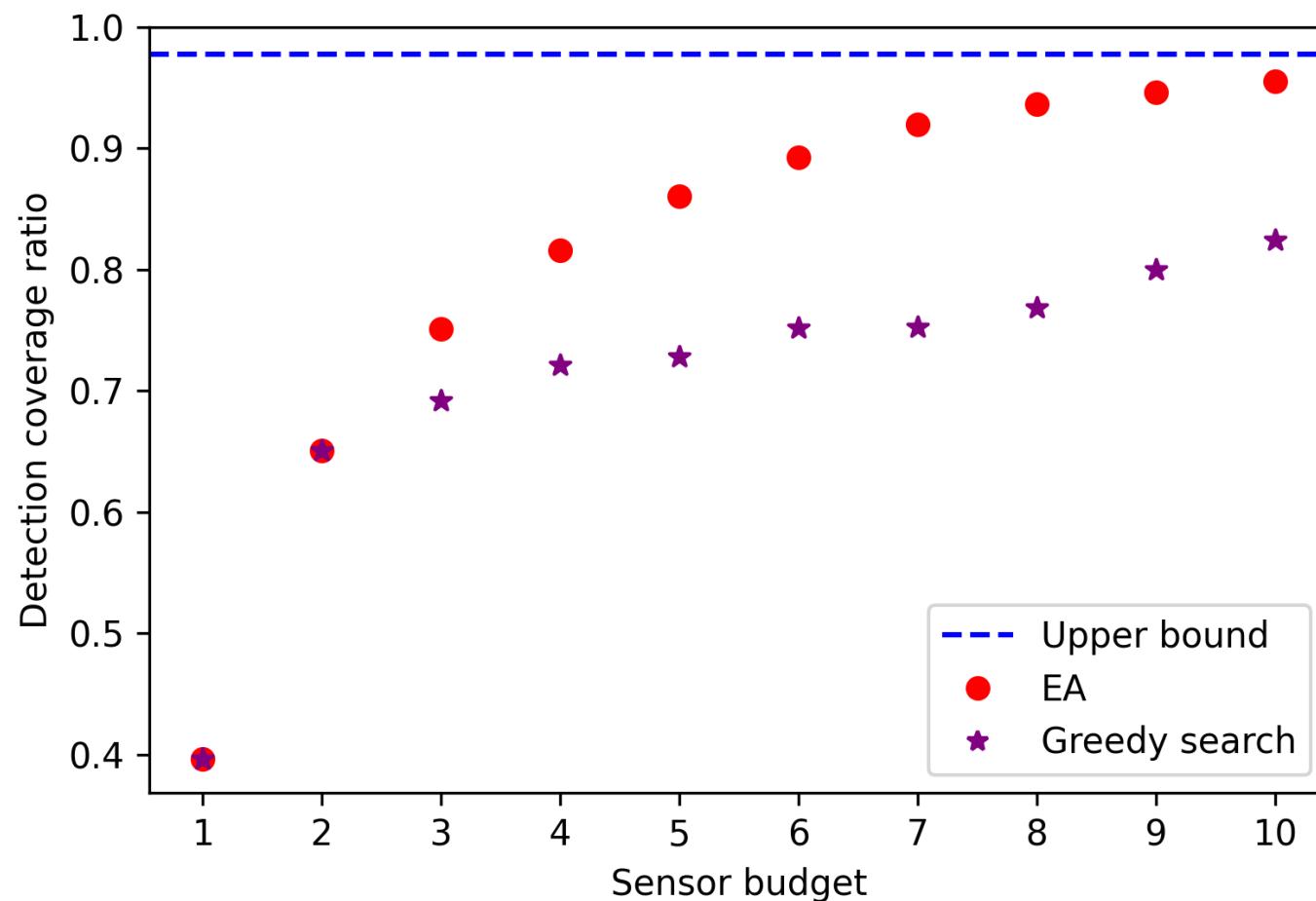
$t = t + 1$

return $\operatorname{argmax}_{x \in P, |x| \leq k} g(x)$

$u > z \iff$
 $g_1(u) > g_1(z) \text{ & } g_2(u) \geq g_2(z)$
or
 $g_1(u) \geq g_1(z) \text{ & } g_2(u) > g_2(z)$

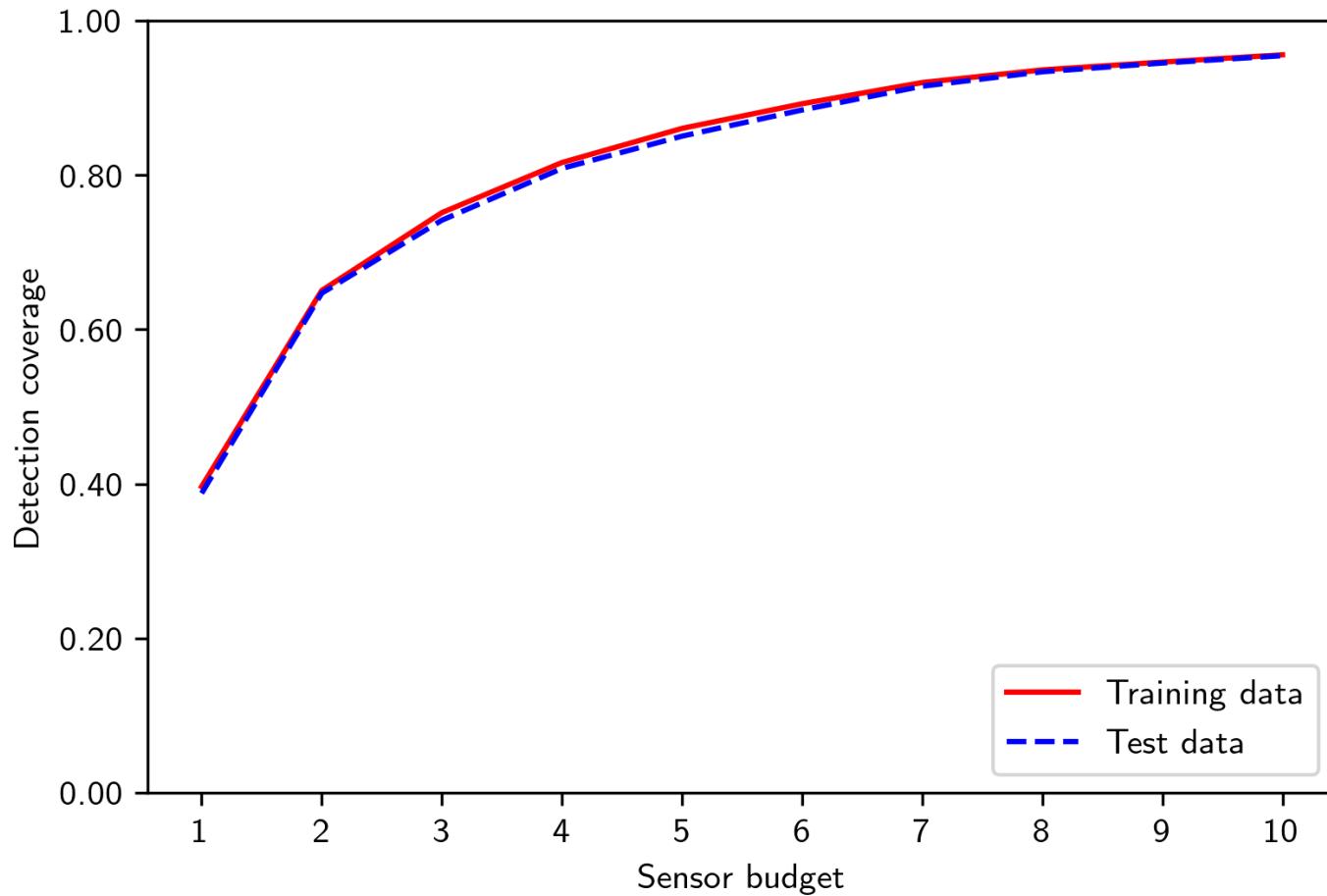
EA vs. Greedy Search

- EA vs. greedy search

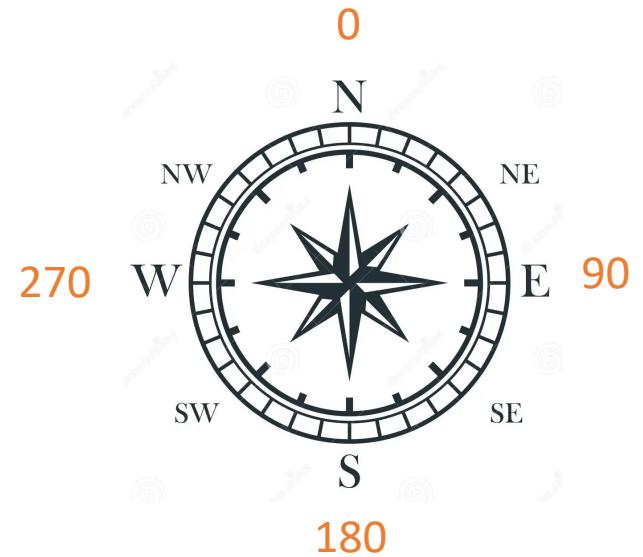
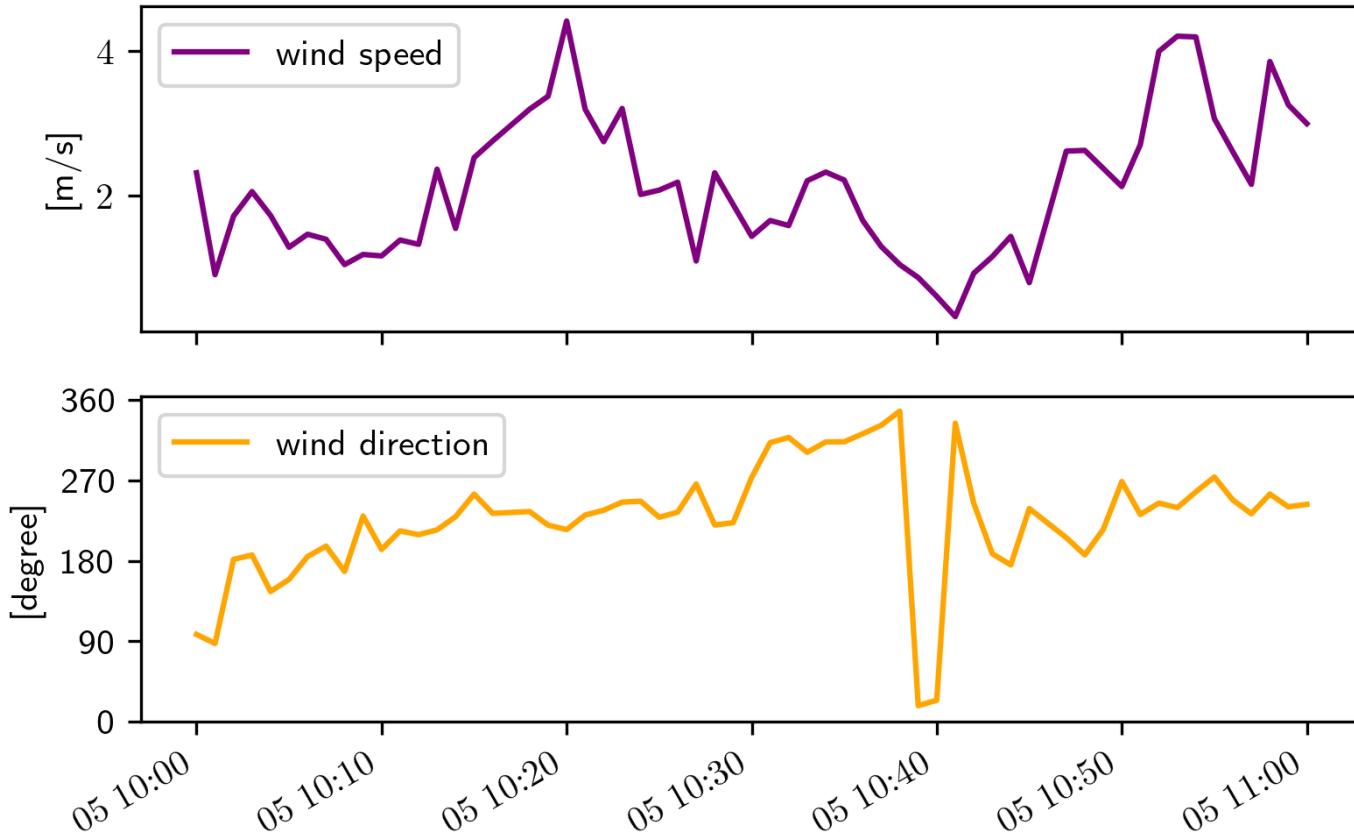


Experiments & Results - robustness

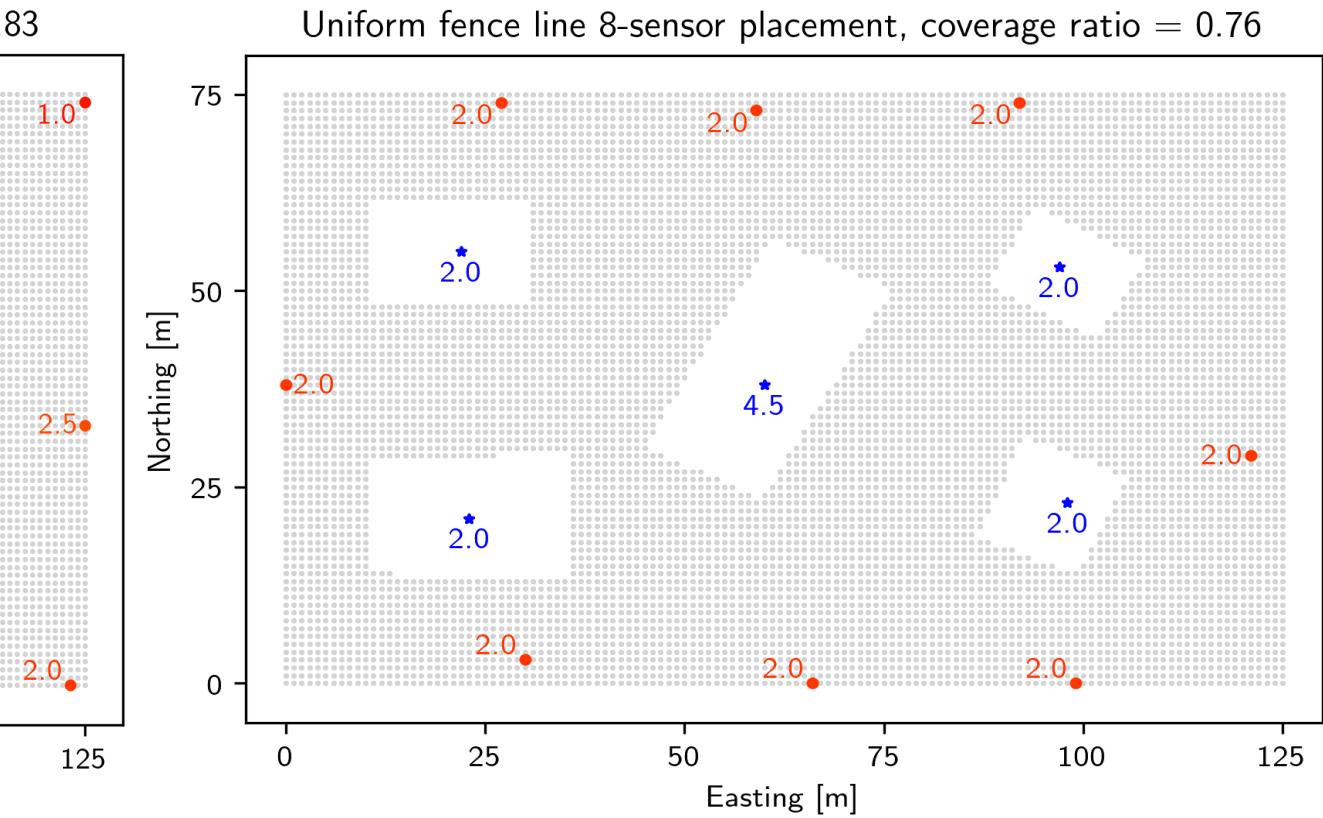
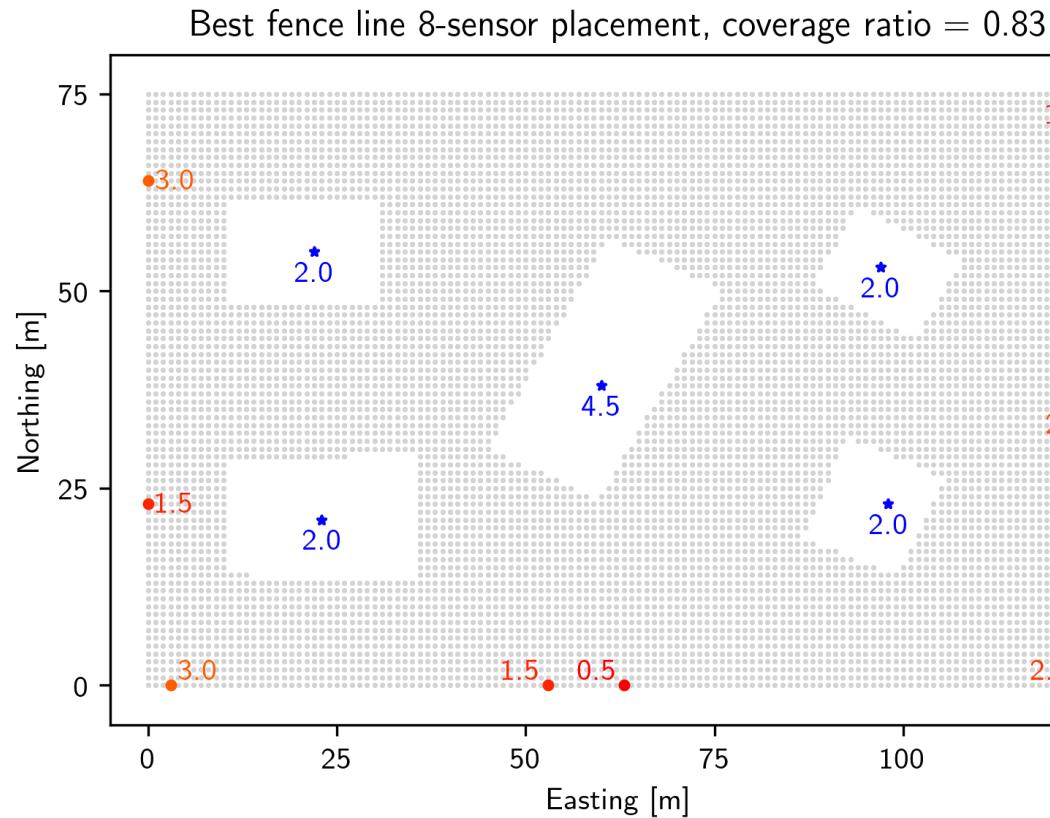
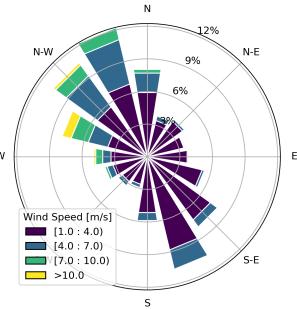
Use a different set of 10,000 emission scenarios to validate the performance of the optimal sensor placement.



Why some scenarios are always undetected?



Experiments & Results – fence line placement

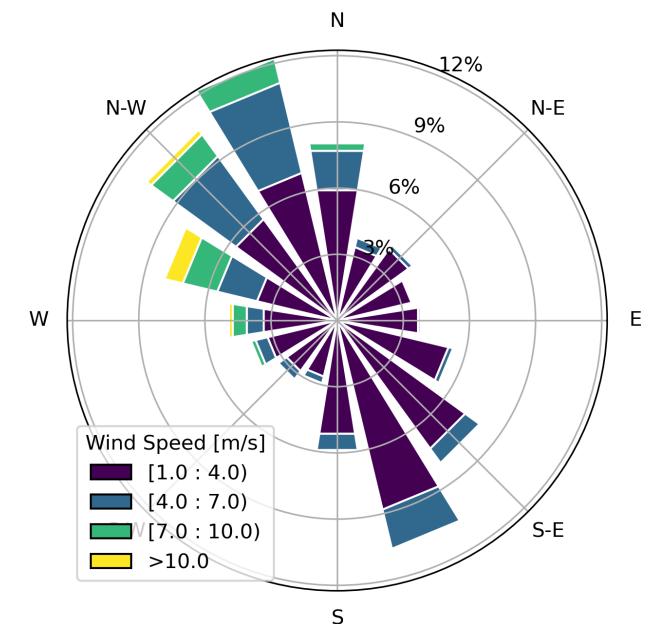
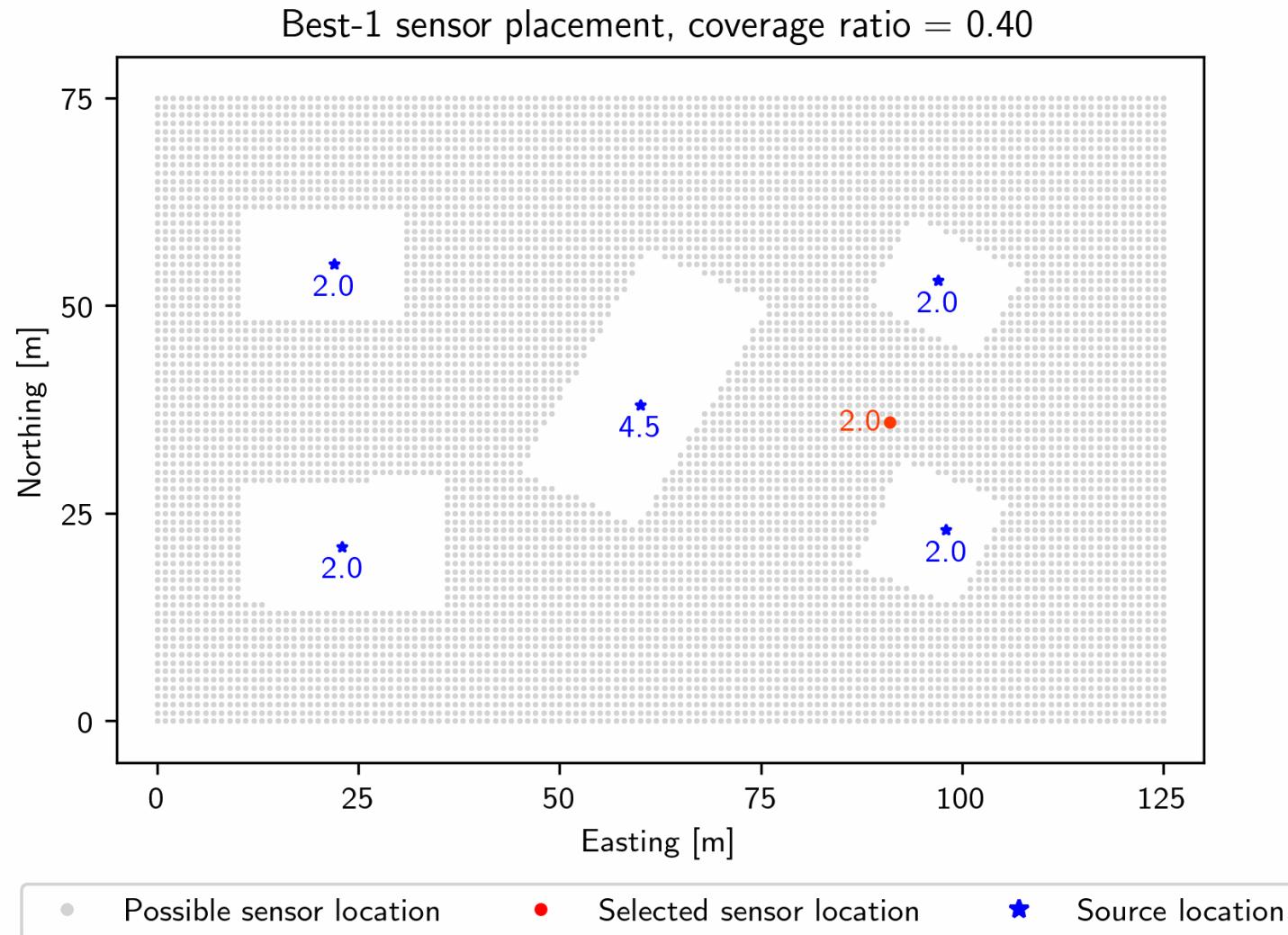


● Possible sensor location

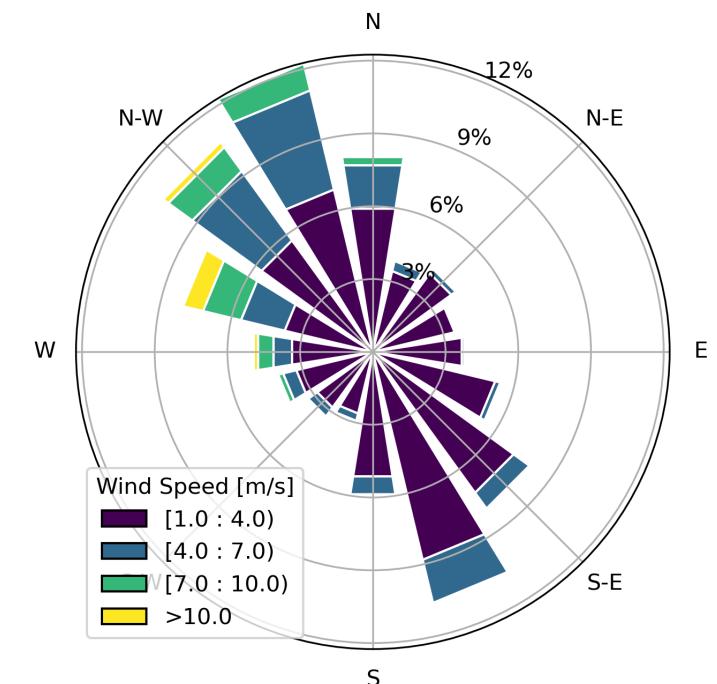
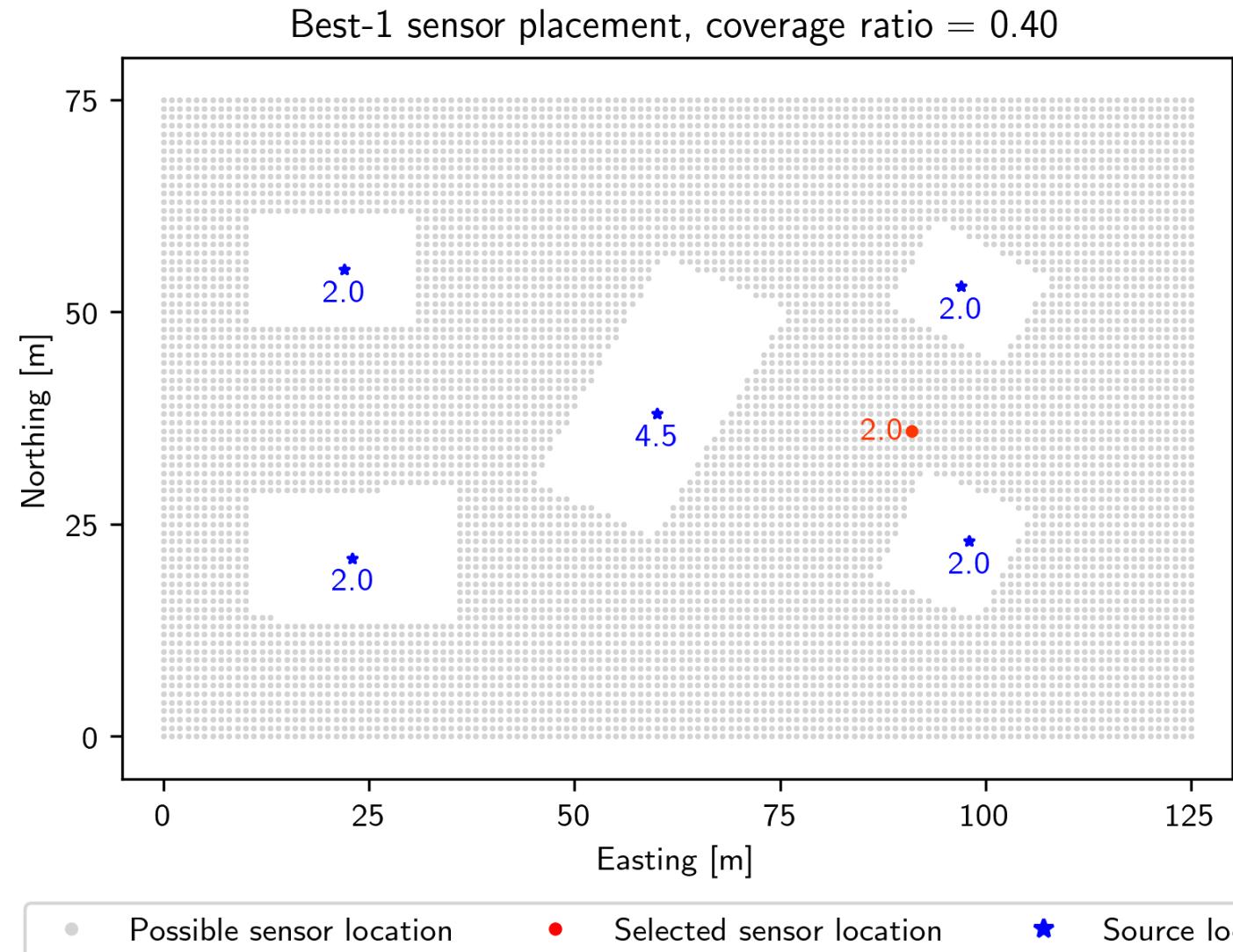
● Selected sensor location

★ Source location

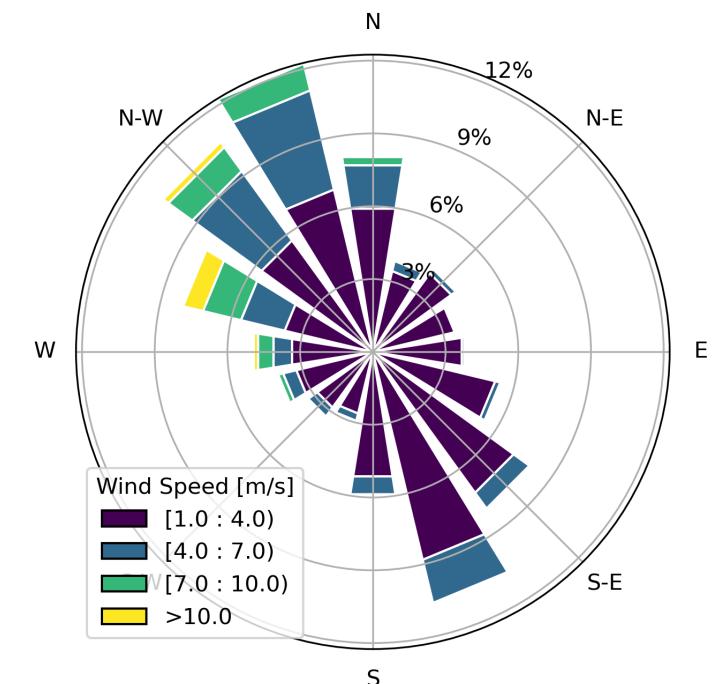
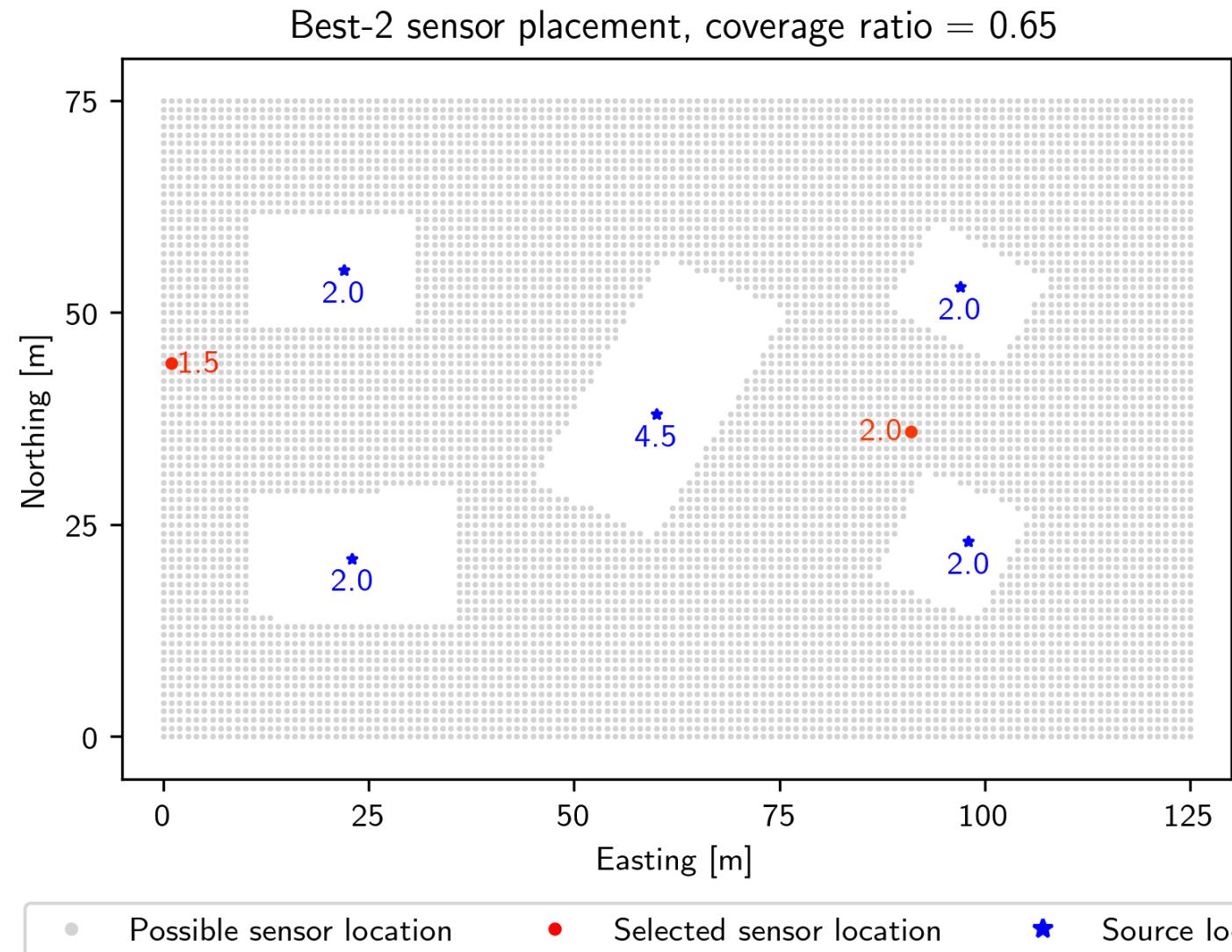
Results: Best k -sensor placement



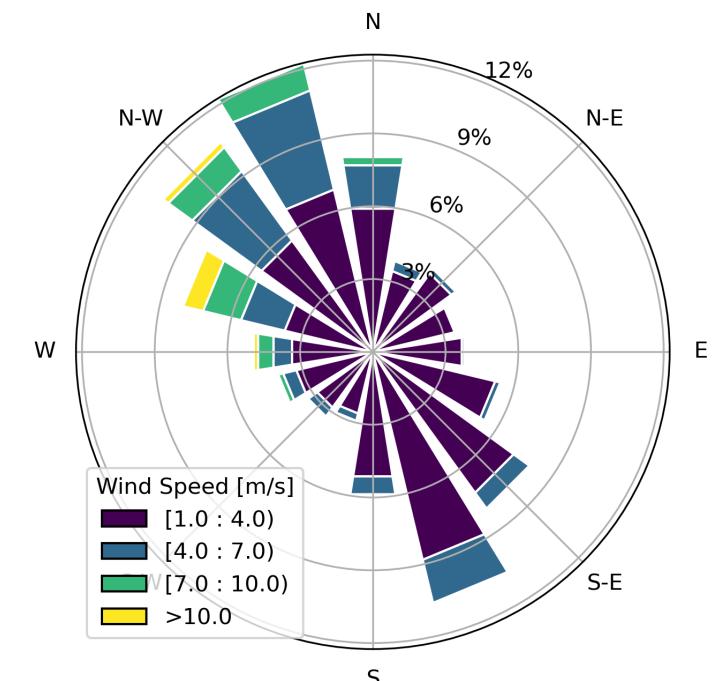
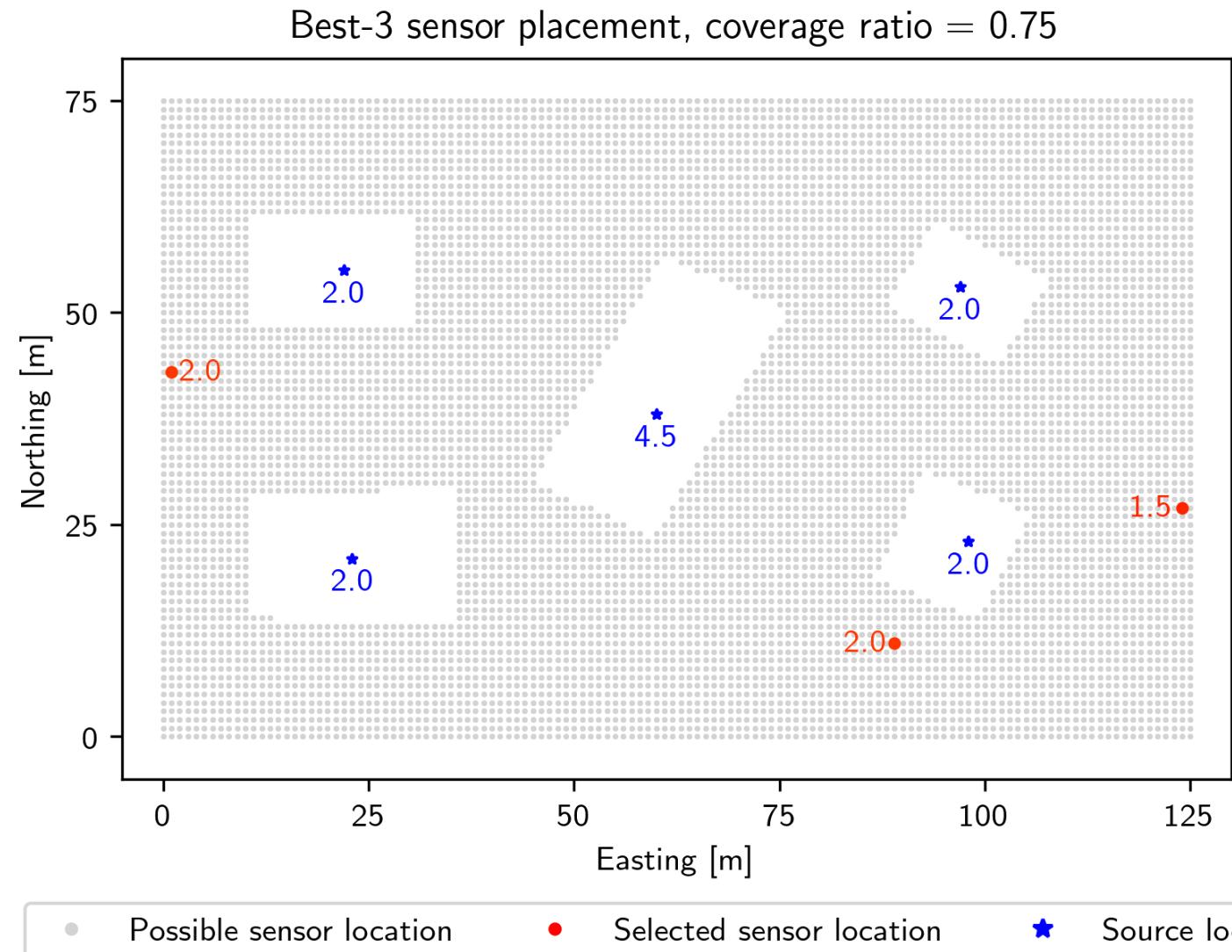
Best-1 Sensor Placement



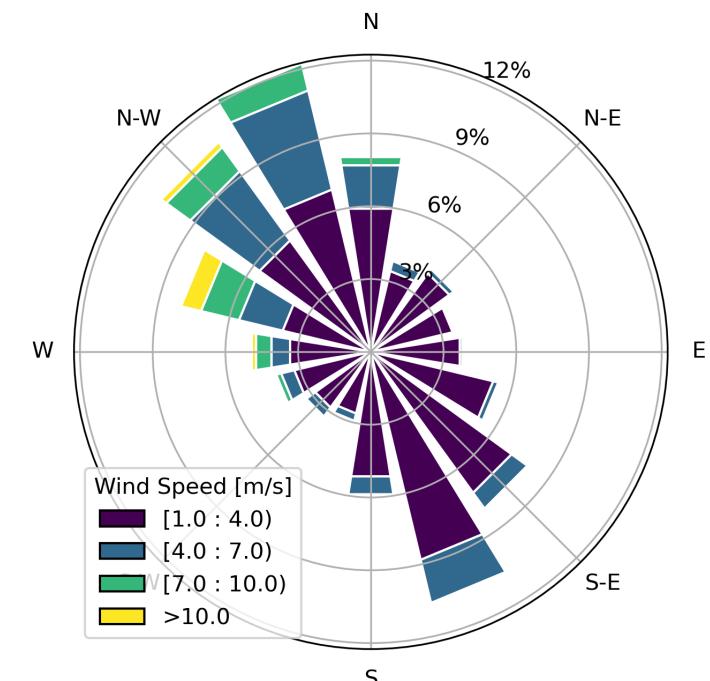
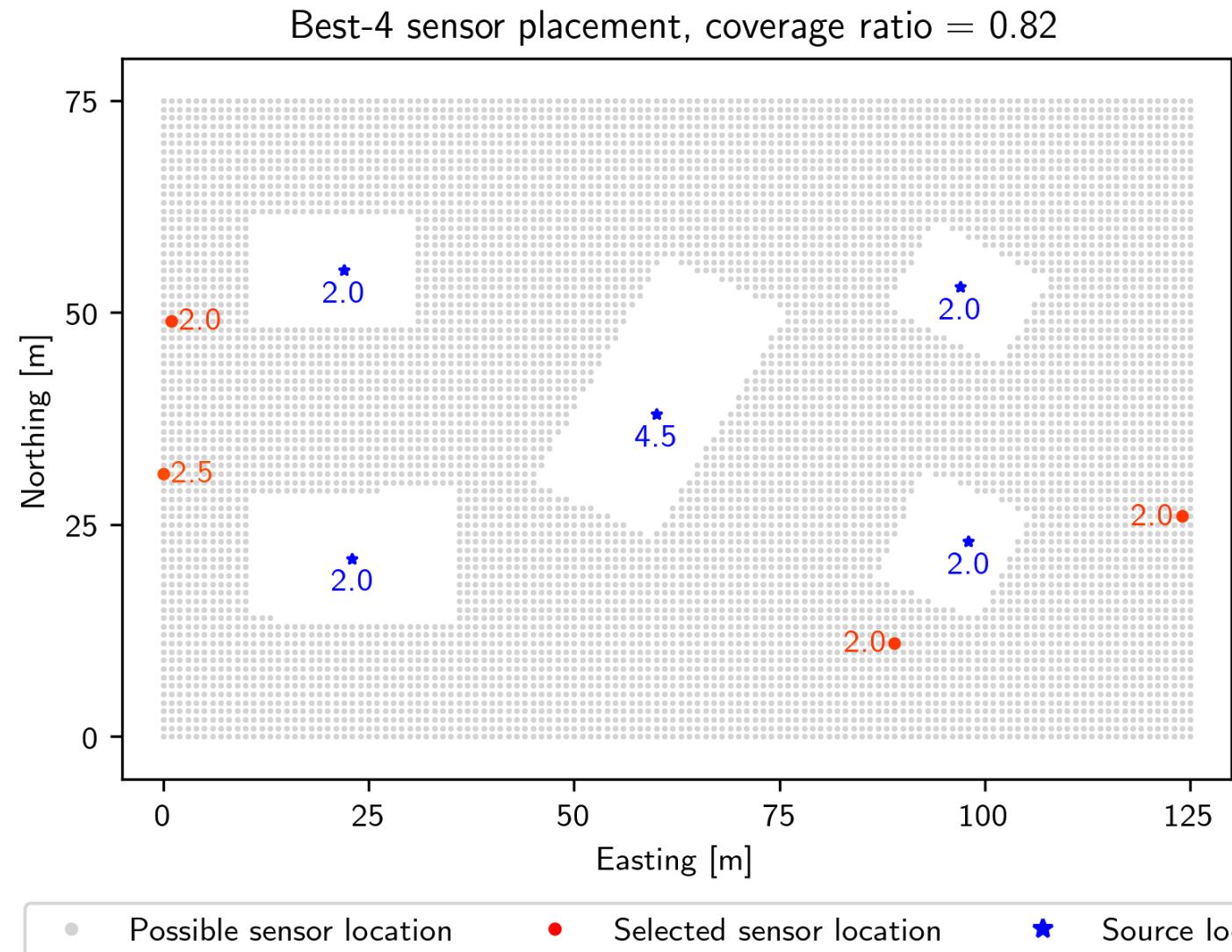
Best-2 Sensor Placement



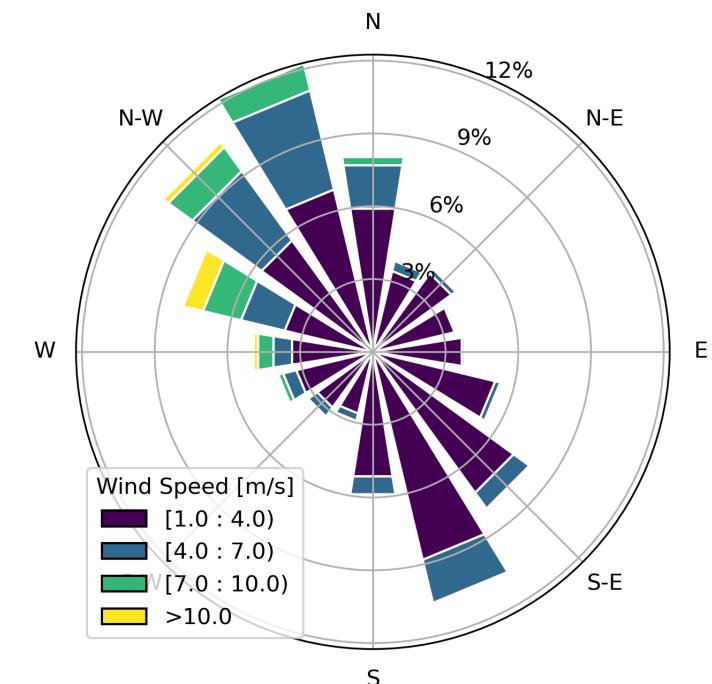
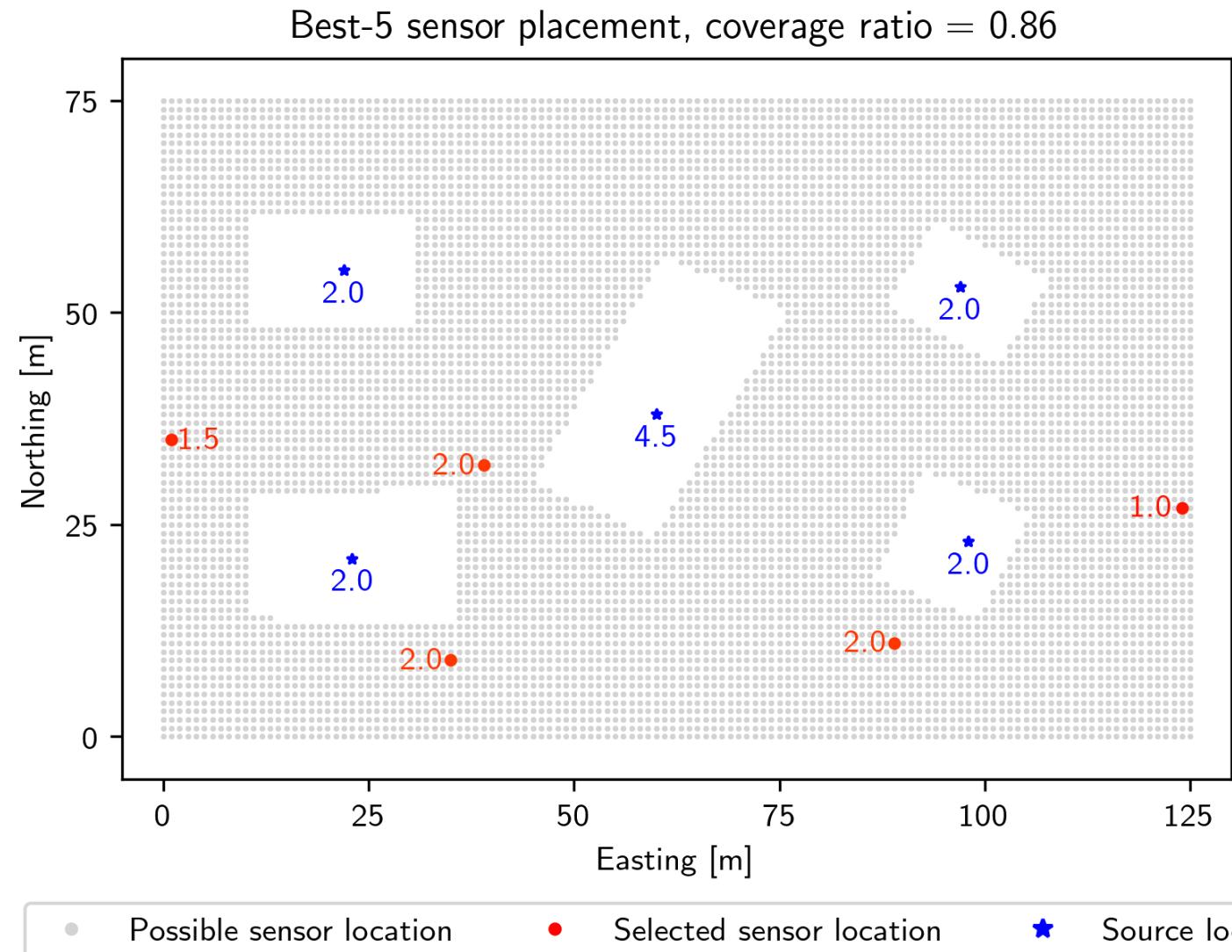
Best-3 Sensor Placement



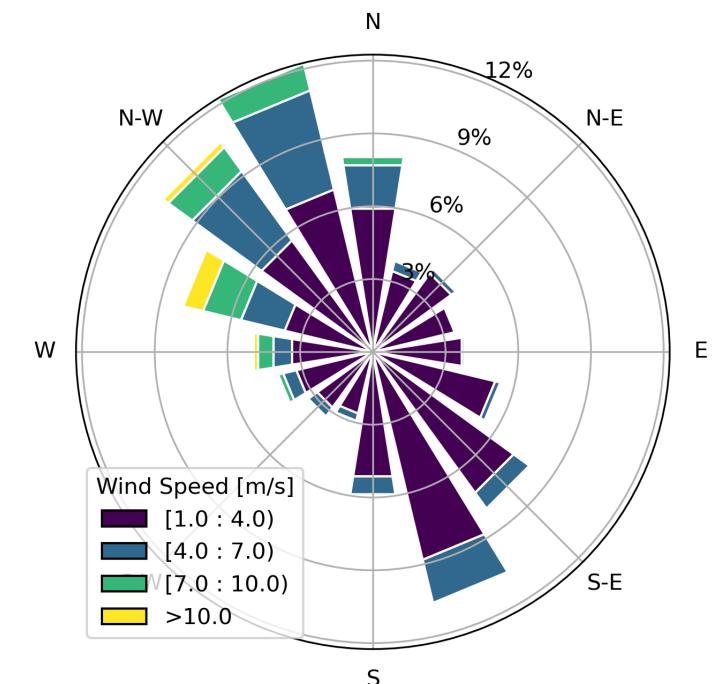
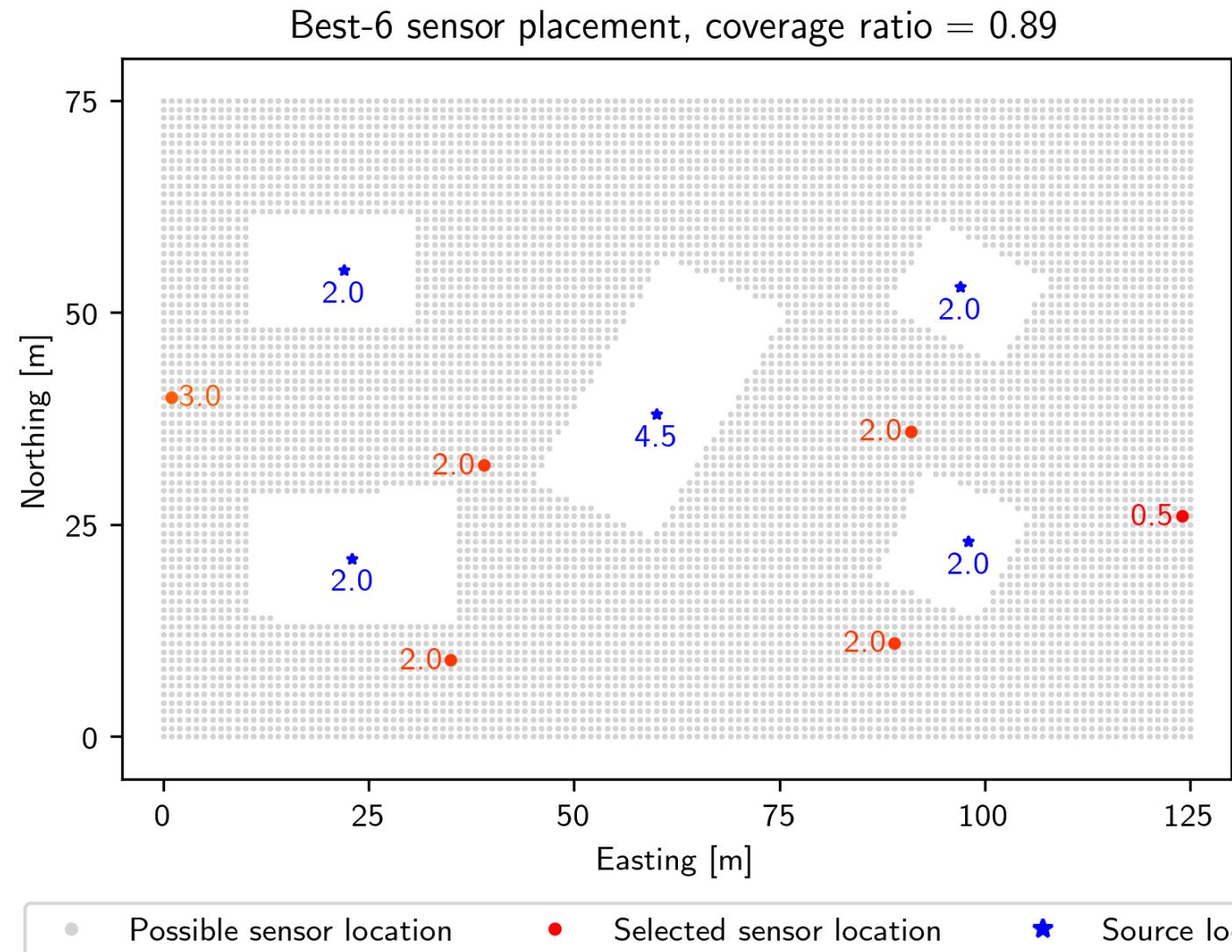
Best-4 Sensor Placement



Best-5 Sensor Placement

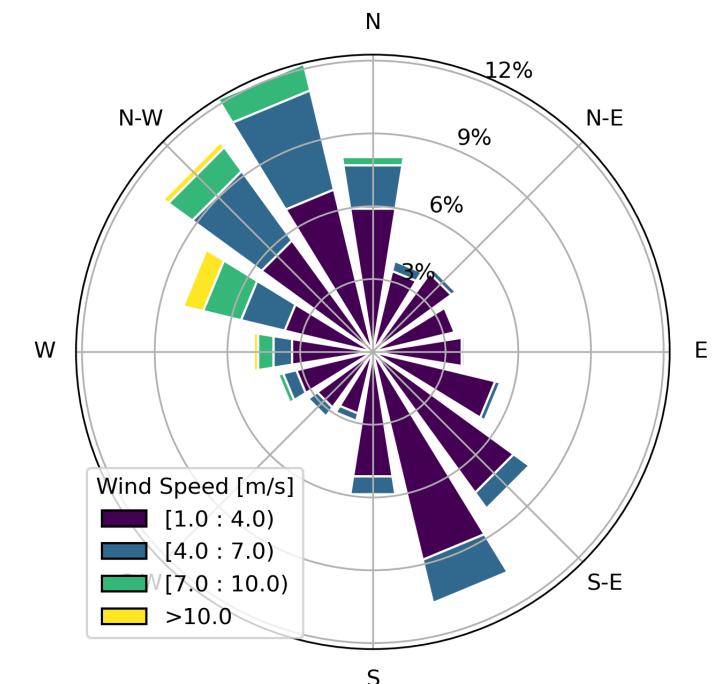
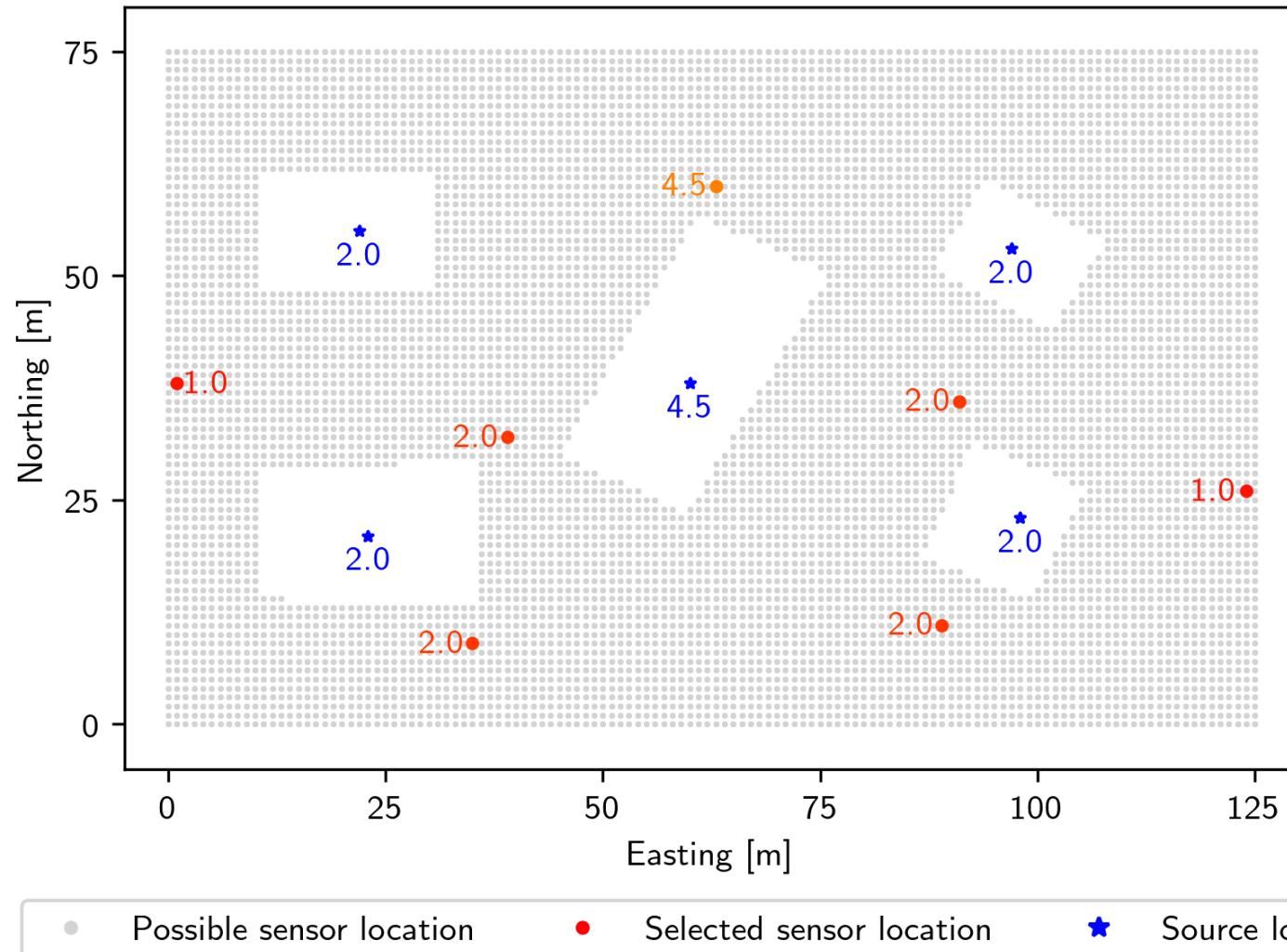


Best-6 Sensor Placement



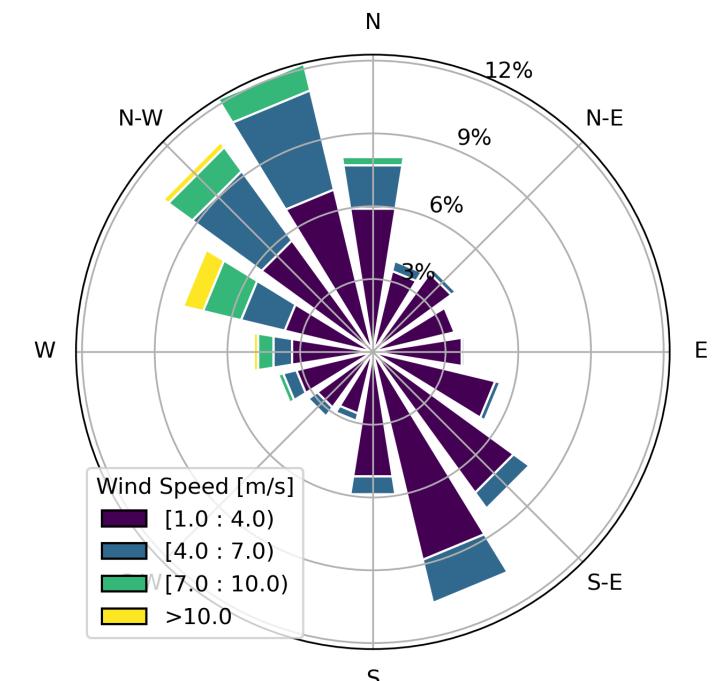
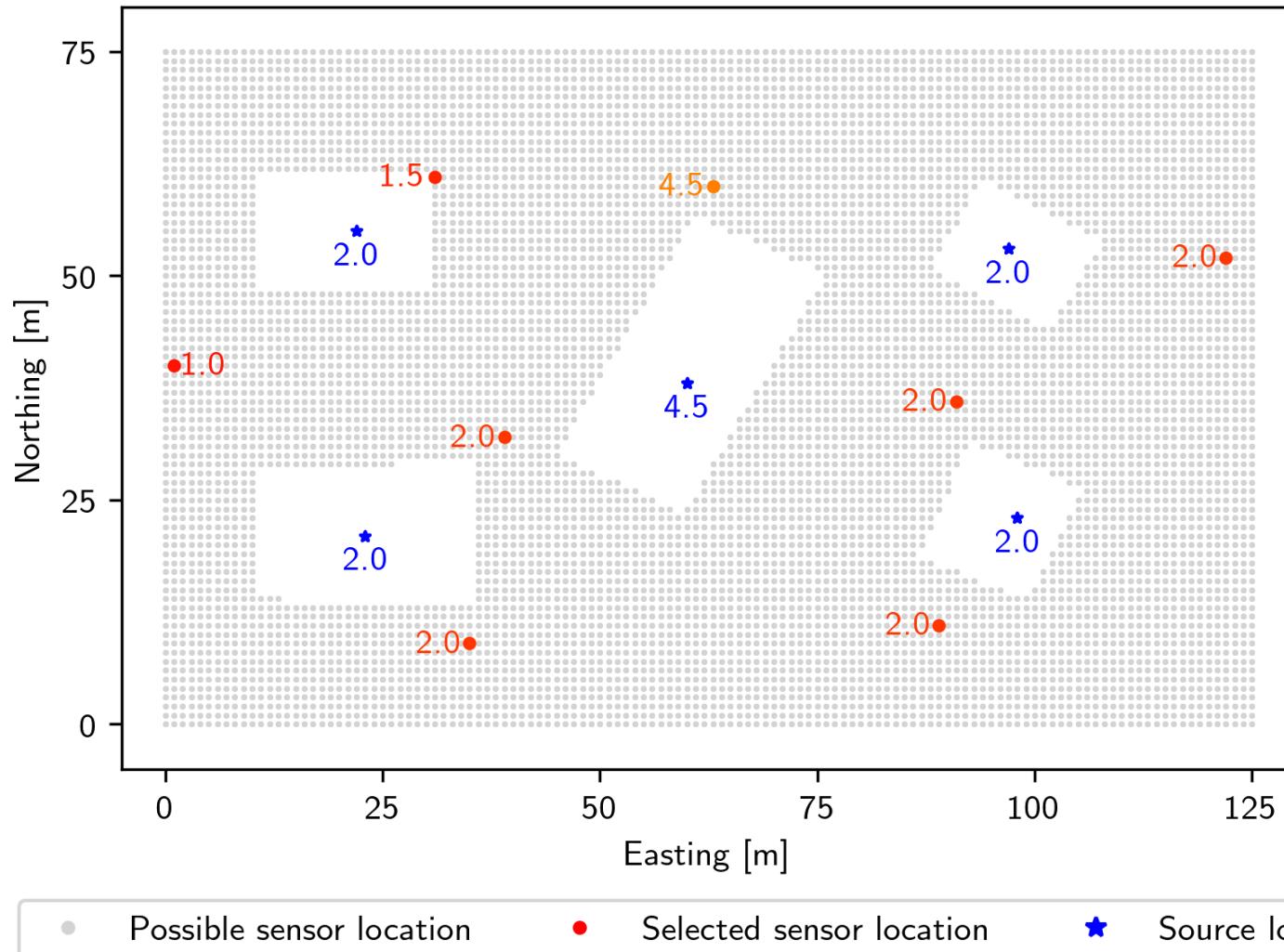
Best-7 Sensor Placement

Best-7 sensor placement, coverage ratio = 0.92

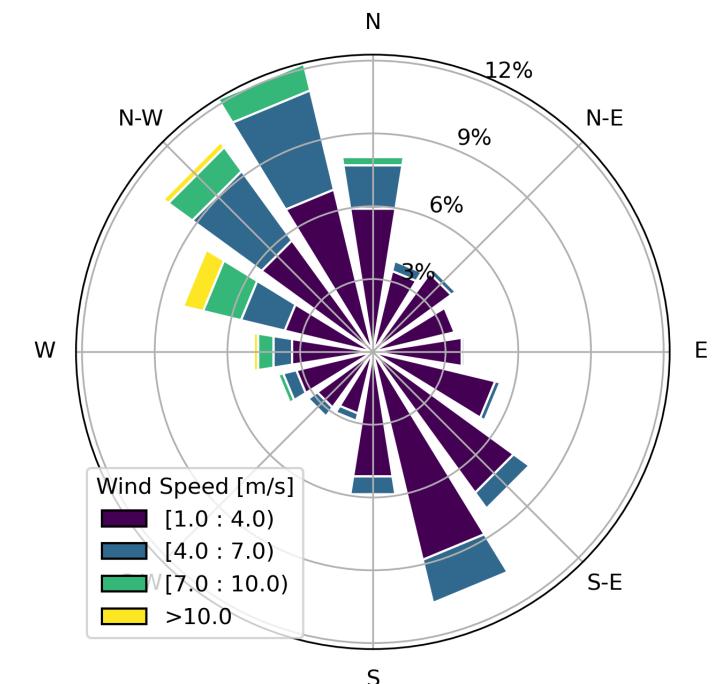
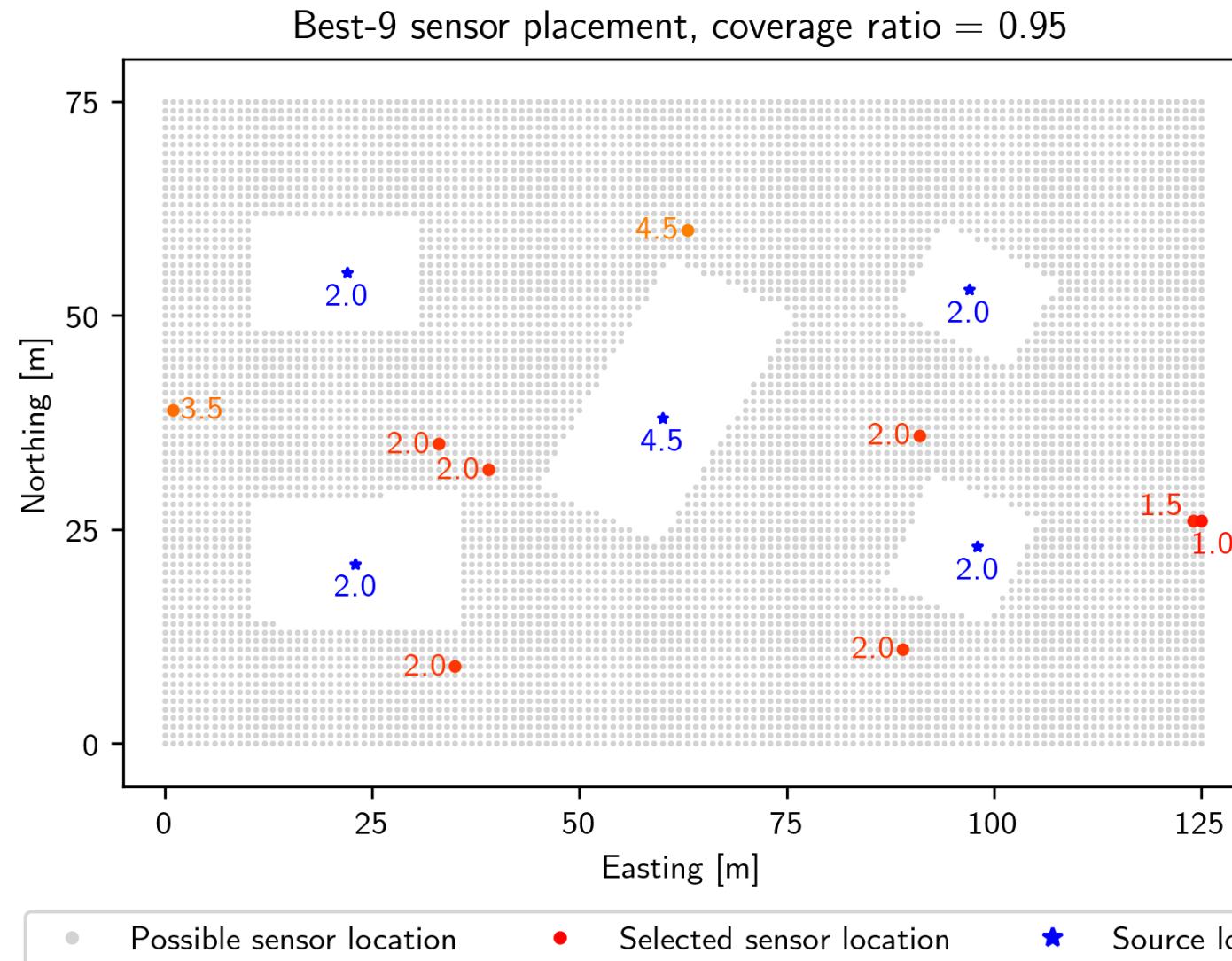


Best-8 Sensor Placement

Best-8 sensor placement, coverage ratio = 0.93



Best-9 Sensor Placement



Best-10 Sensor Placement

Best-10 sensor placement, coverage ratio = 0.96

